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EFFECTS OF A GAMIFIED SELF-MONITORING APP ON HOUSEHOLD FOOD WASTE REDUCTION

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ABSTRACT

Food waste is a global issue, with approximately half of this waste occurring at the consumer stage. In this study, we focused on refrigerator management behaviors in Japan and conducted an intervention study involving 126 households assigned to intervention and control groups, based on the Motivation–Opportunity–Ability (MOA) framework. Four target behaviors were established: “searching for food that should be used sooner,” “moving such food to visible places,” “using food that should be used sooner,” and “finishing meals.” To promote these behaviors and reduce food waste, a gamified self-monitoring intervention using a behavior-recording app was implemented. The study included three two-week measurement periods: a baseline period, an intervention period, and a follow-up period conducted three months after the intervention. Food waste was measured using a cloud-based automatic weighing system that recorded data every hour, and participants were instructed to separate avoidable food waste and dispose of it in designated bins. The average weekly food waste per household decreased by 190 g (45%) in the intervention group and by 60 g (13%) in the control group, corresponding to a 32 percentage-point difference between groups. A general linear model (GLM) with bootstrap inference, controlling for baseline food waste, indicated a statistically significant reduction in food waste in the intervention group compared with the control group. Among six selected behavioral indicators, four showed significant intervention effects. However, no significant associations were observed between behavioral changes and changes in food waste in the main effects model. More than 90% of participants in the intervention group used the app five or more days per week, and subjective evaluations suggested increased motivation and relatively low perceived burden. These findings demonstrate the effectiveness of a gamified self-monitoring intervention for reducing household food waste.

1. INTRODUCTION

1.1 Background

One-third of the world’s food production is wasted (FAO, 2013), significantly impacting climate change, food insecurity, and resource waste (Jobson et al., 2024). Consequently, the United Nations Sustainable Development Goal (SDG) 12.3 sets an international target to halve food waste by 2030 (United Nations, 2015). Achieving this goal requires implementing effective prevention measures to enable consumers to reduce their food waste (Casonato et al., 2023).

Nonomura (2020) and Porpino (2016) identified behaviors influencing household food waste generation, including unplanned shopping, improper storage methods during preservation and management, forgetting food items in the refrigerator, inadequate management of leftovers, and over-preparation or leftovers during consumption. Among countermeasures for these behaviors, refrigerator management actions to use up stored food in the refrigerator differ from shopping behaviors or storage and cooking techniques. Failure in refrigerator management directly leads to discarding food. Proper management, however, holds significant potential to reduce the unused ingredients and leftover food that constitute a large portion of food waste (Hebrok & Boks, 2017; Waitt & Phillips, 2016; Yamakawa, 2020).

Initiatives to encourage household food waste reduction behaviors often rely on information provision (He-

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brok & Boks, 2017; Stöckli et al., 2018; Yamakawa, 2020). However, informational interventions are generally considered to have limited effectiveness (Casonato et al., 2023; Simões et al., 2022; Stöckli et al., 2018). Non-informational interventions include those utilizing nudges or environmental modifications through physical devices (Boulet & Lauren, 2024; Cooper et al., 2023; European Commission Joint Research Centre, 2023; Farr-Wharton et al., 2014b; van der Werf et al., 2021; van Herpen et al., 2023), and food management apps based on information and communication technology (ICT) (European Commission Joint Research Centre, 2023; Farr-Wharton et al., 2014a; Ganglbauer et al., 2013; Mathisen & Johansen, 2022; Vogels et al., 2018). Smartphones are readily accessible to many consumers; therefore, interventions utilizing smartphone apps and similar tools hold significant potential for reducing household food waste (Castro et al., 2023). Furthermore, ICT tools and apps are expected to be powerful tools for policy implementation, as they have the potential to reach consumers across various socioeconomic strata (Vogels et al., 2018).

In our previous research, the use of smartphone photography and food management apps as ICT tools had a marginally significant effect on reducing food waste. The previous study identified three target behaviors within refrigerator management actions to help use up stored food, including “search for food that should be eaten sooner”, “move it to a visible place”, and “use the foods that should be eaten sooner”. The results suggested that these actions improved refrigerator organization and effectively reduced food waste (Seta et al., 2025). On the other hand, using a food management app for refrigerator inventory management presented challenges related to the burden of data entry. Additionally, the motivation to use the app and to reduce food waste relied solely on information provision. Consequently, reducing the burden when utilizing ICT tools and developing interventions to motivate users beyond information provision are key challenges. This study examined two non-informational intervention strategies to address these challenges: (1) self-monitoring to directly promote target behaviors and (2) interventions utilizing gamification to increase motivation.

1.2 Literature review

1.2.1 Interventions involving self-monitoring

Interventions that track behaviors can be considered a form of self-monitoring. Self-monitoring involves tracking one’s performance by recording actions and their outcomes, thereby gaining information about both past and present behaviors (Nkwo et al., 2021; Orji & Moffatt, 2018). Self-monitoring has applications in health and education and has gained recognition as an effective tool for behavioral change (Guo, 2022; Michie et al., 2009; Morrow et al., 2022; Page et al., 2020). When faced with an objective, self-monitoring leads to self-awareness of the gap between the goal and the current state, thereby activating motivation to bridge that gap. In experiments within the food waste field, the food waste diary (hereafter referred to as the diary) serves as an equivalent to self-monitoring. In a journal format, the diary is intended primarily to measure food waste volume by recording discarded food items and the reasons for disposal (Ganglbauer et al., 2012, 2015; Hartikainen et al., 2025). Moreover, reporting food waste is also expected to increase awareness of waste volume, thereby potentially reducing it (Visschers et al., 2016).

Pelt et al., (2020) examined three intervention groups: an information-only group, an awareness group combining information with a one-week diary, and a dissonance-based group involving persuasion and planning tasks. In this study, researchers provided information and instruction to all the participants through door-to-door interventions. Quantitative analysis of food waste through composition analysis showed no effect of the diaries on reducing food waste in the awareness-based group. However, descriptions in the participants’ diaries indicated an impact on their awareness. The one-week diary period may have been too short to instigate behavioral change. This situation leaves unresolved the potential of self-monitoring through recording personal behavior to foster awareness and behavioral change. Furthermore, although a diary may be intended to be used solely for measurement purposes in intervention studies, it may still contribute to reducing food waste (Leverenz et al., 2019). Studies examining the impact of self-reporting using direct measurements also found that the more frequently measurements were taken, the greater the reduction in food waste (Ramos et al., 2024).

In addition, digital technologies have been introduced into households in ways that involve recording or measuring food-related activities, which are conceptually similar to self-monitoring. Roe et al. (2022) conducted a technology-assisted intervention in which participants used an application to photograph waste items in order to measure food waste while receiving individualized reduction advice from a coach. Plate waste in the intervention group decreased by 78.8% compared with the baseline period, and this reduction was statistically significant. In contrast, total avoidable food waste decreased in both the intervention and control groups; although the intervention group showed a 46.6% reduction, the difference was not statistically significant.

Similarly, Qi et al. (2023) asked participants to use a photo-recording application for nutritional monitoring. Their results suggested that the act of measurement itself produced incidental learning effects about food waste generation, thereby increasing awareness and contributing to reductions in food waste. Although these studies were not explicitly designed as self-monitoring interventions, they share conceptual similarities with food waste diary studies and can be regarded as forms of self-monitoring in which recording (through photographs) is conducted primarily for measurement purposes.

Wada and Shinagawa (2018) conducted a study with university students using a self-evaluation sheet for food waste reduction behaviors. Participants recorded whether they implemented eight reduction behaviors during the purchasing, cooking, and consumption stages over a one-week period. Questionnaire surveys assessing perceptions and awareness regarding food waste were administered before and after the intervention to analyze changes in awareness. The results showed a significant difference in "cooking only what can be eaten," with additional changes observed in awareness related to using up ingredients, eating all prepared food, and keeping track of refrigerator contents. However, the study examined changes in awareness rather than behavioral outcomes, and food waste quantities were not measured.

Although intervention studies using self-monitoring to reduce food waste remain limited, some evidence suggests a degree of effectiveness. However, such approaches impose a non-negligible burden on participants, including estimating or measuring food waste quantities in diaries and recording reasons for disposal. From the perspective outlined in Section 1.1, these approaches may be difficult to implement as practical interventions in their existing forms. On the other hand, a simple recording of reduction behaviors, as in the approach of Wada and Shinagawa (2018), is expected to reduce participant burden. At present, few studies have employed a control-group design to evaluate a self-monitoring intervention specifically aimed at reducing household food waste while directly measuring waste quantities.

1.2.2 Gamification-based Interventions

Another challenge identified in Seta et al. (2025) is the need for motivational approaches beyond information provision. In recent years, the use of gamification to positively motivate behavior has increased (Riar et al., 2022; Santos et al., 2025). Gamification refers to the application of game design elements to non-game contexts to increase motivation and engagement (Deterding et al., 2011; Huotari & Hamari, 2017). Common game elements (strategy types) used to increase motivation include points, badges, and leaderboards (Hamari et al., 2014; Soma et al., 2020). Points visualize a user's engagement and experience within the game and are considered a form of reward (Mathisen & Johansen, 2022; Zichermann & Cunningham, 2011). Badges are visual indicators of progress, serving as motivators, psychological rewards, and goal-setting tools (Kyewski & Krämer, 2018; Zichermann & Cunningham, 2011). Leaderboards display players' score rankings and are used for individual goal-setting, but they also increase motivation through competitive awareness by comparing players within the game (Landers et al., 2017; Zichermann & Cunningham, 2011). Approximately half of the current research on gamification has been in educational settings, followed by health and physical exercise. In studies that established a control group and performed quantitative analysis, over 60% showed positive results (Koivisto & Hamari, 2019).

A notable study applying gamification to reduce food waste at home was undertaken by (Soma et al., 2020). They implemented an intervention using an online game that reinforced information. In the game, the participants earned points by correctly answering food waste quizzes and received monetary rewards based on their points. Two other types of informational intervention groups and a control group were also established. They reported that although the game group's food waste was approximately 30% lower after the campaign, the between-group difference in changes in food waste levels was not statistically significant (Kruskal–Wallis H = 3.69, p = .30), and only a marginal within-group change was observed (one-tailed p = .07). The game group comprised 26 participating households, and food waste volume was measured using composition analysis. One possible explanation for the lack of statistical significance, despite the relatively large reduction, is the small sample size of the intervention group. Whether gamification effects can be detected as statistically significant with larger sample sizes remain an open question.

Other research on consumer-oriented app development and usability evaluation suggests impacts on awareness and knowledge; however, the effectiveness of such interventions in reducing food waste has not been empirically verified (Haas et al., 2022; Venessa & Aripradono, 2023).

Although not employing gamification, another relevant line of research has framed food waste reduction behaviors as "missions," a concept commonly used in games (Cooper et al., 2023). Cooper et al. (2023) introduced a weekly "Use-up day," during which participants were asked to prepare a meal using foods that needed to be consumed soon. In this study, the intervention motivated participants by reframing food waste reduction as an opportunity to create an additional meal from ingredients already available at home. The intervention was designed based on the Motivation–Opportunity–Ability (MOA) framework: the use-up day created opportunities for action, while simple practical guidance for using up food was provided to enhance participants' abilities.

Several variations of the intervention group were implemented; however, the overall results showed that in the first experiment food waste decreased by 14.4% from the baseline in the control group, whereas the intervention group showed a 33.4% reduction, with a significant interaction effect identified using linear mixed-effects models. In the second experiment, food waste decreased by 8% in the control group and by 46% in the intervention group, again with a significant interaction effect. These findings suggest that structured interventions targeting specific food management behaviors can reduce household food waste. However, food waste amounts in this study were estimated using questionnaire data, and the weight of food waste was not directly measured.

Further, the results of Soma et al. (2020) suggest that a gamified intervention to reduce household food waste may be effective. Although their results did not reach statistical significance, the gamification group exhibited a comparatively larger reduction than the other groups, despite relying primarily on knowledge-based quizzes that did not directly promote reduction behaviors. This suggests the potential of gamification to facilitate food waste reduction, although the effects of game elements cannot be clearly distinguished from those of monetary incentives.

In the context of the current study, gamification-based interventions are considered to have the potential to enhance motivation and engagement in pro-environmental behaviors. From the perspective of the MOA framework, such approaches may enhance motivation through engagement mechanisms, while behavior recording can facilitate opportunities and abilities for improved food management.

Taken together, these findings suggest that structured self-monitoring interventions targeting food management behaviors (as in Cooper et al.) and gamification-based approaches (as in Soma et al.) may provide complementary pathways for reducing food waste. The issue of participant burden identified by Seta et al. (2025) may be addressed by adopting self-monitoring through the recording of target behaviors, which is expected to impose a relatively low burden. At the same time, the need for motivational approaches beyond information provision may be addressed by incorporating gamification and designing interventions based on the MOA framework, thereby potentially achieving greater reductions in food waste. However, to the best of our knowledge, no studies have combined gamification elements with self-monitoring based on the recording of food management behaviors and evaluated their effects on household food waste reduction using directly measured data.

1.3 Purpose of this study

Based on the considerations in Section 1.2, this study aims to quantitatively analyze the effectiveness of an intervention that combines self-monitoring through the recording of target behaviors with gamification, using food waste weight measurement data from the intervention and control groups, and to clarify its impact on related behaviors.

2. MATERIALS AND METHODS

2.1 Intervention design

2.1.1 Conceptual framework and target behaviors

Figure 1 presents the conceptual framework of food management behaviors aimed at reducing food waste in this study. We conceptualize six behaviors representing key aspects of household food management, corresponding to a sequence of processes from refrigerator management to consumption and purchasing.

Within this process, refrigerator organization behaviors such as "searching" for food and "moving" food to a visible place are expected to enhance awareness of food stored in the refrigerator, referred to here as inventory knowledge. Improved inventory knowledge may facilitate the "prioritized use" of food that should be consumed soon and promote "finishing meals." Furthermore, it is also expected to influence purchasing behavior, contributing to "preventing over-buying."

Among these behaviors, three—"prioritized use of food that should be used sooner," "finishing meals," and "preventing over-buying"—are considered to be more directly related to food waste generation. When these behaviors are not performed, the likelihood of food being discarded increases. Previous studies have also identified the absence of these behaviors as major contributors to household food waste (Ananda et al., 2024; Boulet et al., 2023; Principato et al., 2021).

For the intervention, four of the six behaviors were selected as target behaviors. Following the approach of Seta et al. (2025), the behaviors "search," "move," and "use" were adopted, and "finishing meals" was additionally included. The first three behaviors correspond to the "use" of food that should be consumed soon and supporting actions that facilitate this behavior. Together, they simplify refrigerator management into a straightforward sequence of searching, moving, and using food items. These actions are easy to implement, have potential for widespread adoption, and represent a combination of behaviors perceived as effective, with demonstrated potential to reduce food waste (Seta et al., 2025; Yamakawa, 2020). In addition, "finishing meals" was included to address plate waste, which is an important component of household food waste (Okayama et al., 2021).

Based on this framework, while the intervention targets these four behaviors, all six behaviors—including "inventory knowledge" and "preventing over-buying," which are considered important within the process of food waste reduction—were included in the analysis. Although inventory knowledge has aspects of a psychological state variable, acquiring such knowledge is considered part of the behavioral sequence of refrigerator management in this study. Therefore, it is included among the six food management behaviors examined in the analysis.

Finally, it should be noted that Figure 1 illustrates the conceptual relationships among these behaviors. However, due to data limitations, this framework was not tested using mediation analysis. Instead, as described in Section 2.2, the analysis was conducted based on a simplified set of hypotheses.

2.1.2 Theoretical framework for intervention strategies

Following Seta et al. (2025), the MOA framework (Ölander & ThØgersen, 1995) was adopted as the theoret-

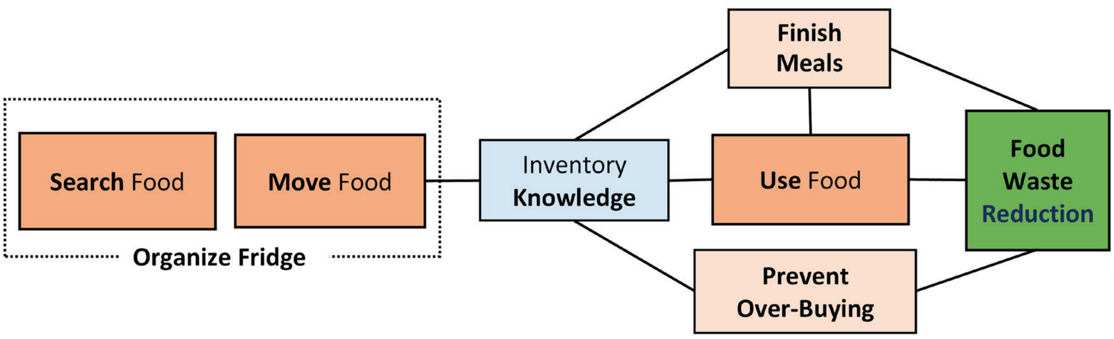


FIGURE 1: Conceptual framework of food management behaviors for food waste reduction.

ical basis for designing intervention strategies. The MOA framework posits that motivation, opportunity, and ability are necessary for action. It is frequently used as a theoretical framework for designing interventions aimed at reducing household food waste and has demonstrated effectiveness (Cooper et al., 2023; Seta et al., 2025; Soma et al., 2021; von Kameke & Fischer, 2018; Van Herpen et al., 2023). In our previous intervention using the support tools, the focus was on ability (A) within the MOA framework, specifically improving knowledge and skills for refrigerator management, whereas opportunity (O) was created through the use of support tools. Motivation (M) was addressed solely through an informational intervention (Seta et al., 2025). This study also used informational intervention to influence motivation. Additionally, it employed a non-informational intervention, tracking one's own behaviors in a food waste reduction self-monitoring app (hereafter, the self-monitoring app), to create opportunities for the target behaviors. Furthermore, it aimed to further enhance motivation for the target behaviors through game elements integrated into the app. Regarding ability, participants were generally considered to possess the necessary skills for the target behavior. Therefore, it was hypothesized that changes in motivation and opportunity would prompt behavioral change. Furthermore, it was expected that the target behaviors would promote refrigerator organization and improve inventory knowledge, and that this ripple effect would enhance the ability to manage food, leading to further reductions in food waste.

2.1.3 Intervention Method 1: Information provision

The informational intervention for participants in the intervention group was delivered by holding an online briefing session (with an option to watch a recorded version) held one week prior to the start of the app-based intervention period, as described in Section 2.1.4. The session covered the importance of refrigerator management for reducing food waste and introduced simple, actionable practices, namely the "search," "move," and "use" behaviors. It also included instructions on how to use the self-monitoring application designed to encourage these target behaviors.

During the two-week intervention period, participants were asked to use the application and engage in efforts to reduce food waste. A leaflet containing the same information presented in the briefing session was also prepared and distributed to all households in the intervention group. In contrast, participants in the control group were asked to continue their usual routines during the intervention period, as in the baseline period. All participants were instructed to dispose of any food waste in the designated bin during the intervention period, in the same manner as during the baseline period. Approximately three months later, during the follow-up period, participants in both groups were asked to maintain their usual routines and to dispose of any food waste generated in the designated bin.

2.1.4 Intervention Method 2: Food waste reduction self-monitoring app

As a non-informational intervention, participants were asked to use the gamified self-monitoring app designed to support and motivate the practice of four target behaviors: "search", "move", "use", and "finishing meals". The researchers determined the necessary functions and specifications for the app, while the development and image creation were outsourced to a company with experience in similar app development. The app was developed in Japanese. Screenshots of the application interface and its core functions are provided in Appendix A.

The developed app enables daily self-monitoring by allowing users to evaluate and record their level of implementation for five items by answering the following five questions.

1. Did you check for foods to be eaten soon? (corresponding to "search")
2. Did you move the foods to be eaten soon to a visible place? ("move")
3. Did you prioritize using the foods to be eaten soon? ("use")
4. Did you finish eating your meal? ("finishing meals")
5. Did any food waste occur during this day?

Questions 1-4 correspond to the four target behaviors to help reduce food waste and were rated on a three-point scale as "Not great", "So-so", or "Perfect". Question 5 assessed food waste quantity, rated as "Quite a bit", "A little", or "None". For questions 1-3, considering the possibility of eating out, a "Not applicable" button was also provided. Figure 2 illustrates game elements used in the self-monitoring app.

The key game elements of points, badges, and leaderboards (PBL) were incorporated into the app structure. Points (P) were derived from self-assessment during behavior checks. For all five items, high ratings were given 20 points, medium ratings were given 10 points, and low ratings were given 5 points. "Not applicable" was assigned the same 10 points as a medium rating. Daily points were a total of these scores up to a maximum of 100 points. Daily points were displayed immediately after recording, accompanied by a message. This aimed to provide motivation by displaying messages of praise for high performance and messages of encouragement to try harder for lower performance.

Badges (B) were earned based on weekly cumulative scores, with four tiers: Bronze (0-349 points), Silver (350-489), Gold (490-629), and Platinum (630-700). Badges were awarded weekly and reset at the start of each new week, encouraging participants to maintain motivation for the following week.

The leaderboard (L) displayed a list of individual cumulative scores for the week up to that point, ordered from highest to lowest. It was placed on the home screen, which was the first screen displayed each time the user logged into the app.

2.2 Hypotheses

As described in Section 2.1.1, four behaviors—"searching for food that should be used sooner," "moving such food to a visible place," "prioritized use of food that should be used sooner," and "finishing meals"—were defined as the

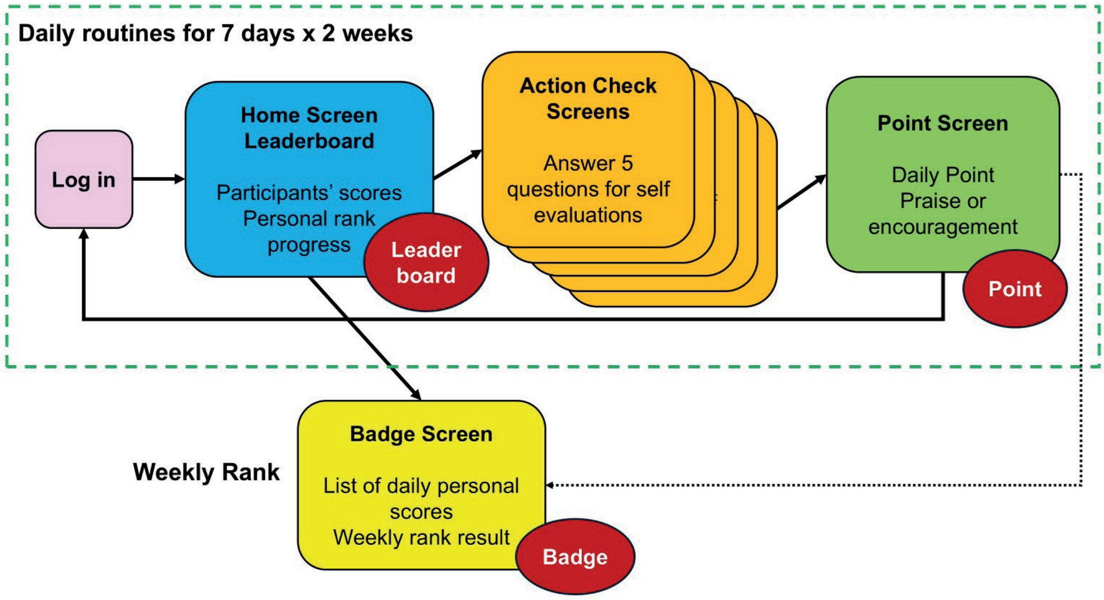


FIGURE 2: Game elements used in the food waste reduction self-monitoring app.

target behaviors of the intervention. In addition, "inventory knowledge" and "preventing over-buying" were included as behaviors to be examined in the analysis.

Although the conceptual framework presented in Figure 1 assumes interrelationships among these behaviors, the primary outcome of this study is the reduction of food waste. Therefore, the research hypotheses were formulated around three key relationships: (1) the effects of the intervention on each behavior (H1 group), (2) the relationship between behavioral changes and food waste reduction (H2 group), and (3) the overall effect of the intervention on food waste reduction (H3). Figure 3 illustrates these three hypothesized relationships as separate analytical components.

When examining the relationship between behavioral changes and food waste reduction (H2), the analysis focuses on three behaviors—"prioritized use of food that should be used sooner," "finishing meals," and "preventing over-buying"—as these are considered to be more directly related to the occurrence of food waste, as indicated in Section 2.1.1.

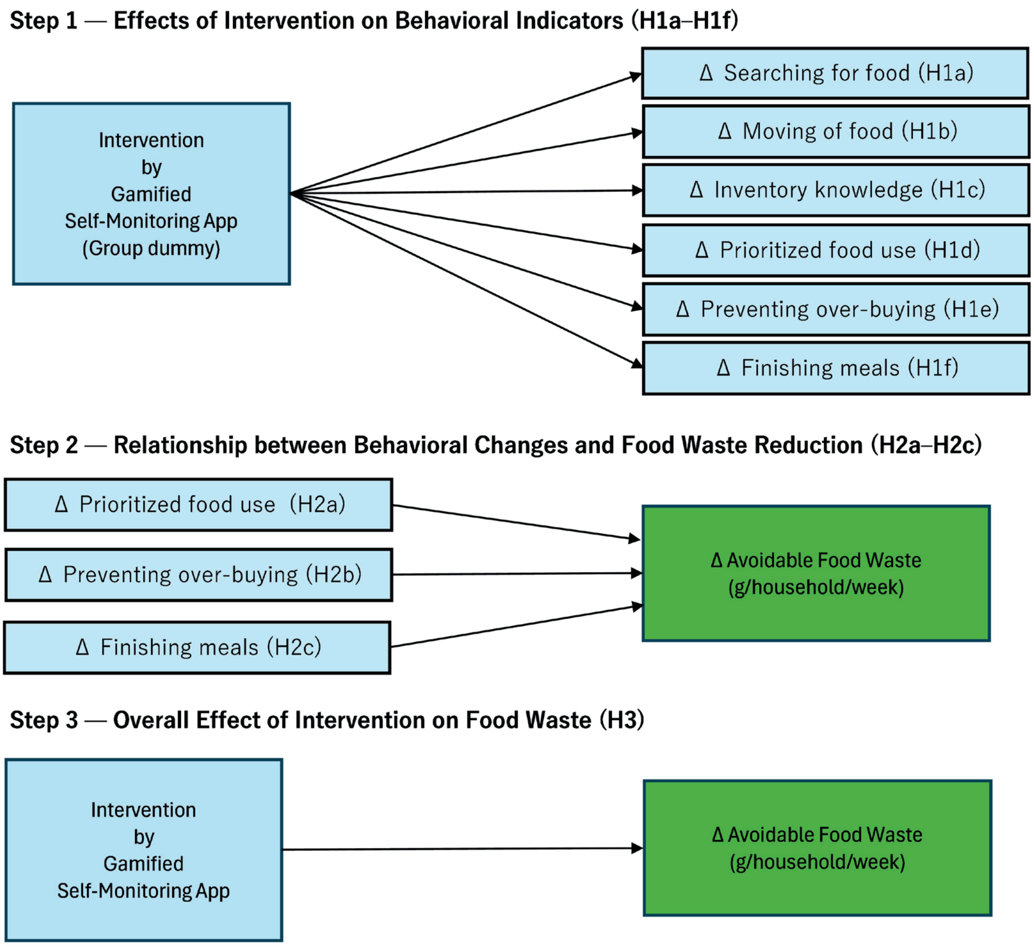
- Hypothesis 1a (H1a): An intervention using the self-monitoring app leads to more frequent searching for food that should be used sooner.
- Hypothesis 1b (H1b): An intervention using the self-monitoring app leads to more frequent moving of food that should be used sooner.
- Hypothesis 1c (H1c): An intervention using the self-monitoring app leads to an increased knowledge of refrigerator inventory.
- Hypothesis 1d (H1d): An intervention using the self-monitoring app leads to more prioritized use of food that should be used sooner.
- Hypothesis 1e (H1e): An intervention using the self-monitoring app leads to a reduction in over-buying.
- Hypothesis 1f (H1f): An intervention using the self-monitoring app leads to more meals being finished.
- Hypothesis 2a (H2a): More frequent prioritized use of food that should be used sooner reduces food waste.
- Hypothesis 2b (H2b): Preventing over-buying reduces food waste.
- Hypothesis 2c (H2c): Finishing more meals reduces food waste.
- Hypothesis 3 (H3): An intervention using the self-monitoring app leads to a reduction in food waste.

2.3 Participants

An a priori power analysis was conducted using G*Power 3.1 (Faul et al., 2007, 2009) to determine the sample size required for verification. For two groups across three periods (baseline, intervention, and follow-up), with a moderate effect size ($f = 0.25$; Cohen, 1988), a significance level of 5% ($\alpha = 0.05$), and a target power of 80% ($1 - \beta = 0.80$), the required total sample size was calculated as 82 participants (minimum 41 per group). For analyses involving two phases (pre- and post-intervention), 130 participants were required (a minimum of 65 per group).

A total of 130 individuals aged 30 or older who prepared meals at home and lived in households with 2 or more members were recruited. To ensure engagement with the intervention, eligibility criteria included the ability to use a smartphone or personal computer to operate the application for two weeks. Recruitment was conducted in September 2024 through municipal newsletters, websites, and other channels in six municipalities in Kyoto Prefecture, as well as through press release websites in Japan; a total of 152 individuals applied from across Japan (88% female). Six individuals whose eligibility could not be verified and 15 who had not disposed of any food waste in the previous two weeks were excluded because the study aimed to evaluate the intervention among individuals who generate food waste. This also helped reduce the prevalence of zero observations in the data.

This study aimed to achieve approximately equal rep-



Note: Δ = change score (intervention period − baseline period). The three steps were analyzed separately; arrows do not represent a single mediation model. Behavioral changes in Step 2 (H2a–H2c) correspond to indicators H1d, H1e, and H1f in Step 1.

FIGURE 3: Hypothesized Relationships among intervention, behavioral changes, and food waste reduction.

resentation across age groups (30s-60s), but applications varied substantially by age group. Because eligibility criteria required the ability to use the application, younger applicants were overrepresented, while relatively few applicants were aged 60 or older. To address this imbalance, 20 applicants in their 30s—where applications were most numerous—were randomly selected for exclusion, resulting in a total of 110 accepted applicants (39 in their 30s, 36 in their 40s, 29 in their 50s, and 6 aged 60 or older). Due to the low number of applicants aged 60s or older, 20 additional participants were recruited from a research company panel, increasing this group to 26. The final enrolled sample was 130 participants; after withdrawals and dropouts, 126 completed the study. Participants who completed the full study period and all three questionnaires received a compensatory gift certificate worth 6,000 yen.

2.4 Experimental procedure

A six-week experiment was conducted between October 2024 and March 2025 (Figure 4), employing a controlled design with systematic allocation. A two-week unit was adopted to reduce variance in food waste measure-

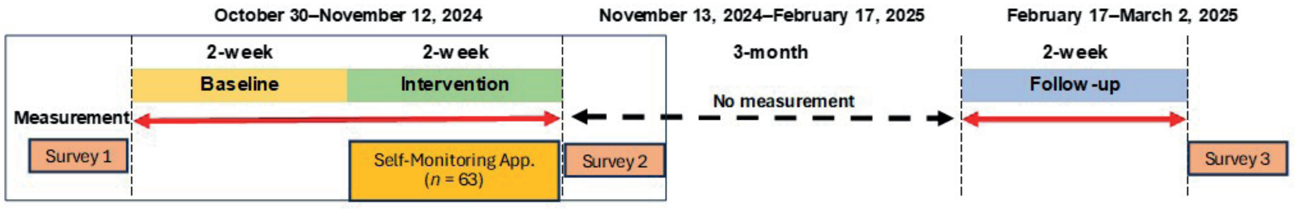


FIGURE 4: Timeline of the experimental procedure (N = 126). Note. The boxed area indicates the period analyzed in the present paper.

ments and limit the frequency of zero observations. During each period, all participants were instructed to separate food waste and dispose of it in designated waste bins. Food waste was measured 24 times per day, at 60-minute intervals, using the cloud-based weighing system.

The first phase of the study consisted of four consecutive weeks: a two-week baseline period during which only measurement was conducted, followed by a two-week intervention period during which measurement continued, and the intervention group used the self-monitoring app. Approximately three months after the end of the intervention period, a two-week follow-up period was conducted, during which only measurements were performed, as in the baseline period. Participants were ordered by age, gender, household size, and food waste frequency. After randomly selecting the starting point, every second participant was assigned to the intervention group, and the remainder were allocated to the control group to achieve approximate balance across characteristics. As a result, 63 households were assigned to each group.

The intervention included a briefing session for the intervention group participants as described in Section 2.1.3. During the two-week intervention period, these participants were asked to use the self-monitoring app described in Section 2.1.4 as a non-informational intervention. Meanwhile, the control group participants were asked to maintain their usual routines during the intervention period.

During the follow-up period, approximately three months after the end of the intervention period, participants in both groups were asked to continue their usual routines while placing any food waste generated into dedicated waste bins.

2.5 Food waste definition and measurement method

In this study, food waste was defined in accordance with the Japanese government's definition as "food that is edible but discarded." The food waste measured in this study was limited to avoidable food waste, consistent with Seta et al. (2025). Following Okayama et al. (2021), avoidable food waste was operationalized as comprising two categories: unused food and leftovers.

When providing instructions to participants, food waste to be measured was defined as plate leftovers, unfinished beverages, remaining prepared foods, and food discarded due to expiration or spoilage. Participants were asked to place such items into a designated waste bin. Inedible parts, such as vegetable or fruit peels, were explicitly excluded. However, for measurement purposes, participants were asked not to place liquids in the dedicated waste bins.

Regarding containers and packaging, if they were lighter than the food itself, they were to be placed in the waste bin as is. If the food contents were lighter than the packaging, participants were instructed to remove the packaging and discard only food contents. While the Japanese government's definition includes excessive removal (see Note 1) in food waste, this study did not. In Japan, household food waste is generally disposed of as combustible waste. Though a small number of municipalities separate food waste for composting, this practice remains uncommon. The measurement method was explained during an online briefing session for all participants before the baseline period began (with the opportunity to view a recorded video). Leaflets summarizing the briefing content were also distributed to all the participating households.

To measure food waste, the cloud-based measurement system used in the study by Seta et al. (2025) was adopted. Specifically, a system combining a 20 L waste container with a mat-type automatic weighing device ("SmartMat", developed by S-Mat, Inc., Tokyo, Japan) was employed, and measurement data were transmitted and collected via a Wi-Fi router in a cloud-based management system. The measurement system is shown in Figure 5. Although the setup resembled organic waste separation for collection, participants were instructed to place only food waste in the designated waste bin.

The cloud-based weighing system conducted automatic measurements 24 times per day at fixed hourly intervals, with data transmitted to the cloud system each time. The weighing device had a maximum capacity of 5 kg, a measurement unit of 1 g, and a maximum measurement error of ±0.15% (2.5 g per 1 kg). As in Seta et al. (2025), a threshold of 5 g was applied, and only increases exceeding this threshold were treated as food waste weight.

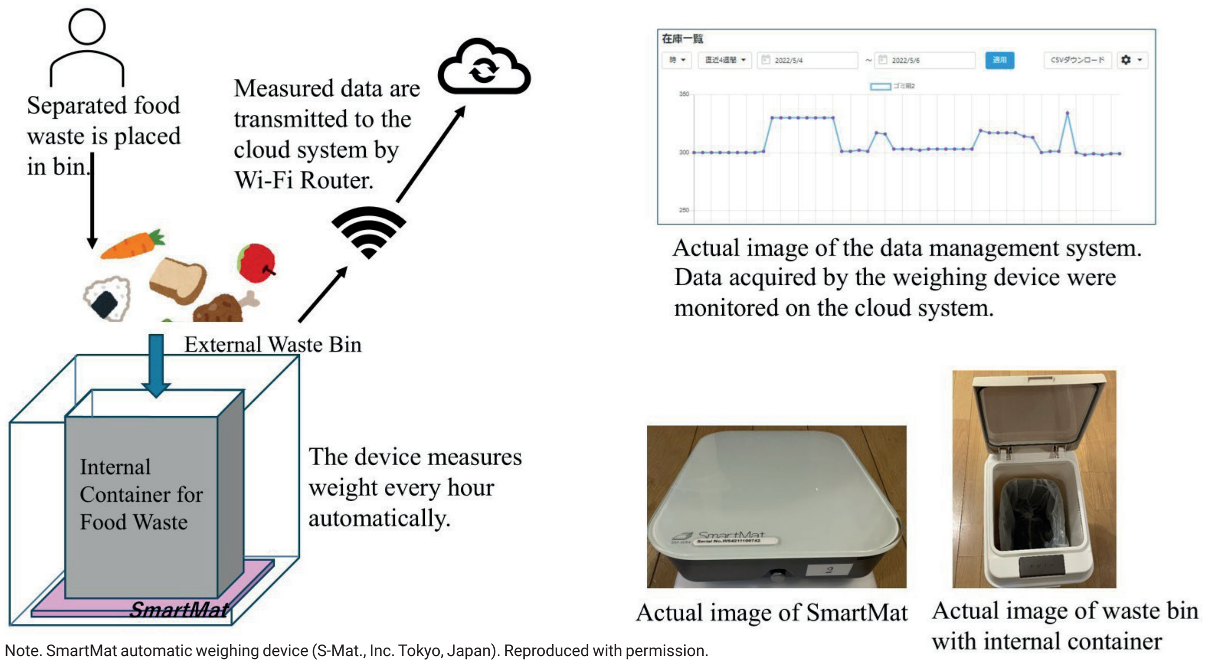
Note 1. Excessive removal refers to the elimination of edible portions during the removal of inedible parts, such as peeling vegetables too thickly.

2.6 Questionnaires

The questionnaire was primarily adapted from the instrument used by Seta et al. (2025). The items were originally developed with reference to previous studies conducted in Japan (Consumer Affairs Agency, 2020; Osaka Prefectural Government, 2019; Yamakawa et al., 2020), but several were modified to fit the experimental design of the present study. The survey was administered online using the Google Forms platform at three points: before the start of the experiment, after the intervention period, and after the follow-up period.

In this study, 13 food management behaviors were measured to assess the extent to which participants engaged in behaviors related to refrigerator management, food use, inventory knowledge, and purchasing behavior. The questionnaire items and response scales used to measure these 13 behaviors are presented in Appendix B. These indicators were designed to capture multiple dimensions of household food management practices.

For hypothesis testing, however, the analysis focused on six behavioral indicators—one for each of the six behaviors specified in the conceptual framework—to ensure interpretability of the analytical model and statistical stability. These six indicators were selected based on their direct correspondence to the intervention target behaviors and their ability to best capture the relevant behavioral construct. Although multiple behavioral indicators were measured for domains such as food use, inventory knowledge, and purchasing behavior, these indicators were not combined into composite scales. This is because each indicator was designed to capture a distinct aspect of food management behavior rather than a single underlying con-



Note. SmartMat automatic weighing device (S-Mat., Inc. Tokyo, Japan). Reproduced with permission.

FIGURE 5: Images of the cloud-based automatic weighing system.

struct. As a result, the correlations among these indicators were not sufficiently strong to justify aggregation based on internal consistency. The remaining indicators were analyzed using descriptive statistics and correlation analysis to provide an overview of behavioral patterns. These results are presented in Appendix D and Appendix E.

The six selected behavioral indicators were: (1) searching for food that should be used sooner, (2) moving such food to a visible place, (3) being aware of expiration dates, (4) prioritized use of food that should be used sooner, (5) buying appropriate quantities, and (6) finishing meals. These six behaviors correspond directly to the conceptual model shown in Figure 1 and the hypothesized relationships presented in Section 2.2 (Figure 3).

Regarding indicator (3), inventory knowledge, effective household food inventory management depends on awareness of both the presence of stored food and its expiration dates. Accordingly, inventory knowledge was operationalized using the item: "During the past two weeks, to what extent did you know expiration dates of the foods stored in your refrigerator?"

For indicator (4), food use behaviors, several indicators were measured; however, "prioritized use of food that should be used sooner" (hereafter, prioritized food use) was selected because it directly corresponds to the intervention target. As for indicator (5), "buying appropriate quantities" was selected from several shopping-related indicators as a representative indicator of purchasing behavior and is treated as synonymous with "preventing over-buying" in subsequent analyses.

Refrigerator organization was measured as a broader indicator encompassing both searching and moving behaviors; however, it was not included among the six indicators as it encompasses two distinct behavioral constructs rather than mapping onto a single intervention target.

Each item of six behaviors was measured on a five-point scale referring to the past two weeks, using frequency for most behaviors and degree for inventory knowledge and finishing meals. These behavioral indicators were analyzed individually as variables corresponding to theoretical constructs. In addition, self-reported food waste frequency was measured using a five-point scale across four categories: plate leftovers, leftover cooked food, partially used ingredients, and unused food items. After the intervention period, participants were also asked whether the requirement to separate food waste influenced their food waste reduction behaviors, using a four-point scale. Details of the questionnaire are provided in Appendix B.

Furthermore, to assess the effects of the intervention on issues commonly associated with ICT-based interventions—such as perceived burden and motivation—participants in the intervention group were asked additional questions after the intervention period regarding their evaluation of the intervention, including perceived burden, motivation, and competitiveness. Details of these items and their results are presented in Appendix C.

2.7 Internet survey by online panels

In parallel with the experiment described in Section 2.4, questionnaire surveys using online panels without food waste measurement were administered. This approach follows the national comparison group approach adopted by Shu et al. (2023), who used it to enhance the precision and reliability of campaign evaluations. In the present study, this method was employed to examine whether the measurement procedure itself influenced participants' behavior.

Online panel participants were selected through a screening survey to match the characteristics of the experimental participants, resulting in 130 individuals, of whom

88 completed all three surveys. The questionnaire items were identical to those used in the experiment, except for items directly related to the experimental procedures. The response period was the same as that for the experimental participants.

2.8 Analysis

In this study, data were collected during the baseline, the intervention, and follow-up periods, conducted three months after the intervention. However, because the primary objective of this paper was to examine the direct effects of the intervention, the analysis was limited to data from the baseline and intervention periods. Data from the follow-up period were not included in the analyses reported here. The long-term effects and persistence of the intervention will be examined separately in combination with previously reported data (Seta et al., 2025).

To examine the hypothesized mechanisms, analyses were conducted in three steps: first, the overall effect of the intervention on food waste was tested (H3); second, the effects of the intervention on food waste reduction behaviors were examined (H1); and third, the relationship between behavioral changes and reductions in food waste was analyzed (H2).

2.8.1 Effect of the intervention on food waste

First, to test Hypothesis H3, the effect of the intervention on food waste was examined. The dependent variable was the change in food waste (intervention period – baseline period), and a general linear model (GLM; i.e., an ordinary least squares regression framework) was estimated.

The independent variable was a dummy variable representing the intervention group (intervention = 1, control = 0). As a covariate, the household's average food waste during the baseline period was included after mean-centering using the overall sample mean. In addition, as an exploratory analysis, a model including an interaction term between the intervention dummy variable and baseline food waste was also estimated.

The change in food waste was used as the dependent variable to directly evaluate the magnitude of change attributable to the intervention while controlling for baseline differences. Baseline food waste was included as a covariate not only to account for regression to the mean but also because participants with low baseline values may have limited reduction potential (floor effects), whereas those with higher baseline values may have greater reduction potential. The interaction model was estimated to examine whether the intervention effect differed depending on baseline food waste levels.

Previous studies have reported that household food waste exhibits substantial variability across households and a highly skewed distribution with many zero values (Van Herpen et al., 2019, 2023; Visschers et al., 2016). Consistent with these findings, the present study exhibited similar distributional characteristics, as discussed in Section 3.1. Given these characteristics, to reduce reliance on the normality assumption and ensure robust statistical inference, standard errors, p-values, and 95% confidence intervals were calculated using a bootstrap procedure stratified by group (intervention vs. control), with 1,000 resamples and percentile-based confidence intervals. Stratification ensured that the group structure was preserved during resampling.

2.8.2 Effect of the intervention on food waste reduction behaviors

Next, to test the hypotheses in H1 (H1a–H1f), the effects of the intervention on food waste reduction behaviors were examined. As in the analysis for Hypothesis H3, estimation was conducted using GLMs. The dependent variables were the changes in the degree of implementation of each of the six food waste reduction behaviors (measured on five-point scales), calculated as the difference between the intervention and baseline periods.

The independent variable was the intervention group dummy variable, and the baseline level of each behavior (mean-centered) was included as a covariate. The rationale for this specification was the same as that described for Hypothesis H3.

To test the six behavioral hypotheses presented in Section 2.6 (H1a–H1f), the corresponding null hypotheses were treated as belonging to the same hypothesis family. To control the inflation of Type I error due to multiple testing, p-values were adjusted using the Holm–Bonferroni procedure.

As non-normality was also observed in the residuals of these models, p-values were calculated in SPSS using percentile-t pivotal tests based on the empirical distribution of studentized bootstrap statistics (1,000 resamples).

2.8.3 Association Between Behavioral Changes and Changes in Food Waste

Next, to test the hypotheses in H2 (H2a–H2c), the relationship between behavioral changes induced by the intervention and changes in food waste was examined. A GLM was estimated using the change in food waste (as defined in Section 2.8.1) as the dependent variable. The model simultaneously included the changes in three behavioral indicators: prioritized food use, finishing meals, and preventing over-buying. These behaviors were selected because they represent proximal food use and purchasing behaviors most directly linked to reductions in household food waste in the hypothesized process model (Figure 3).

By comparing this model with the group coefficient estimates reported in Section 2.8.1, changes in the estimated intervention effect after incorporating behavioral variables were also examined. The group variable was included to control for differences between intervention and control groups.

As in Section 2.8.1, baseline food waste (mean-centered) was included as a covariate to control for initial differences and potential regression-to-the-mean effects. As an exploratory analysis, an interaction model was also estimated to examine whether the effects of behavioral changes varied by baseline food waste levels. This model included interaction terms between each behavioral change varied by baseline food waste levels.

Standard errors, p-values, and 95% confidence intervals were calculated using a bootstrap procedure stratified by

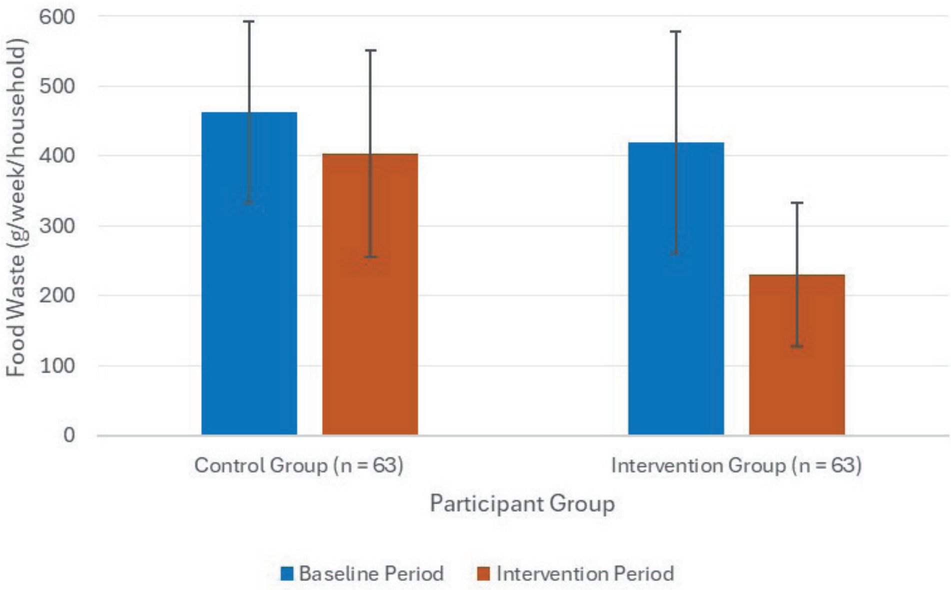


FIGURE 6: Food waste weekly average per household. Error bars represent 95% confidence intervals.

group (1,000 resamples and percentile-based confidence intervals), as described in Section 2.8.1.

2.8.4 Participant Evaluation of the Intervention

The perceived effects of the intervention in terms of reducing perceived burden, enhancing motivation, and fostering a sense of competition were analyzed using descriptive statistics based on evaluations provided by participants in the intervention group. IBM SPSS Statistics 29 was used for the analyses.

This study was reviewed by the Ethics Committee of Kyoto Prefectural University and approved on August 30, 2024 (Application No. 320).

3. RESULTS

3.1 Changes in food waste and effects of the self-monitoring app intervention

Figure 6 presents the average weekly food waste per household during the baseline and intervention periods for both the intervention and control groups, while Table 1 reports descriptive statistics. In the intervention group, food waste decreased by 190 g per household per week from the baseline to the intervention period, corresponding to a 45% reduction. In contrast, the control group showed a decrease of 60 g per household per week (a 13% reduction). Based on these descriptive comparisons, the difference in change between the two groups was 32 percentage points. In both groups, skewness exceeded 2, indicating right-skewed distributions, and excess kurtosis was also high. These results suggest that the distribution of food waste deviated from a normal distribution.

To examine the effect of the self-monitoring app intervention, a main-effects model was estimated using the change in food waste (intervention period – baseline period) as the dependent variable, with an intervention group dummy variable (intervention = 1, control = 0) and baseline food waste (mean-centered) included as predictors (Table 2, Model 1). The GLM was estimated using 1,000 stratified bootstrap resamples. The results indicated that, even after controlling for baseline food waste, the intervention group showed a significantly greater reduction in food waste compared with the control group ($B = -145.42$, 95% CI [−265.56, −17.66], $p = .036$). The 95% confidence intervals were estimated using bootstrap procedures, and the same approach was applied in subsequent analyses. Although deviations from residual normality were observed, statistical significance was evaluated using bootstrap-based confidence intervals that do not rely on the normal approximation, providing robust inference that is not affected by violations of the normality assumption.

Next, to explore potential heterogeneity in the intervention effect, a model including the intervention group dummy variable, baseline food waste (mean-centered),

TABLE 1: Descriptive statistics for weekly household food waste (grams).

Group	Period	N	Mean	SD	Min	Max	Skewness	Kurtosis
Intervention	Baseline	63	419.6	644.1	0	3161.5	2.56	6.92
	Intervention	63	230.1	413.3	0	2500.0	3.66	15.85
Control	Baseline	63	462.7	528.1	0	2528.0	1.77	3.36
	Intervention	63	403.0	598.3	0	3249.5	2.80	9.33

Note. Values are expressed in grams per measurement period.

TABLE 2: Effects of the intervention on change in food waste (stratified bootstrap GLM, n = 126).

Dependent variable: Change in food waste (Intervention – Baseline)				
Model 1: Main Effects				
Predictor	**B**	**Bootstrap SE**	**95% CI**	**p**
Intervention (1 = intervention)	-145.42	64.44	[-265.56, -17.66]	.036
Baseline food waste (centered)	-0.364	0.137	[-0.637, -0.094]	.014
Intercept	-51.83	43.63	[-141.25, 35.84]	.261
Model 2: Interaction Model				
Predictor	**B**	**Bootstrap SE**	**95% CI**	**p**
Intervention (1 = intervention)	-143.03	58.9	[-263.64, -20.42]	.045
Baseline food waste (centered)	-0.035	0.148	[-0.402, 0.177]	.808
Intervention × Baseline food waste (centered)	-0.55	0.224	[-0.949, -0.083]	.028
Intercept	-58.95	37.5	[-138.68, 10.61]	.151

Note. 1,000 stratified bootstrap resamples; two-tailed tests.

and their interaction term was estimated (Table 2, Model 2). The interaction between the intervention group dummy and baseline food waste was statistically significant ($B = -0.55$, 95% CI [−0.949, −0.083], $p = .028$). This result indicates that households with higher baseline food waste experienced larger reductions as a result of the intervention. In the interaction model, the main effect of baseline food waste for the control group was not statistically significant ($B = -0.035$, 95% CI [−0.402, 0.177], $p = .808$), whereas the corresponding effect for the intervention group was significant ($B = -0.584$, 95% CI [−0.917, −0.298], $p = .005$). These results suggest that the influence of baseline food waste differed between the two groups.

Taken together, these results support H3, indicating that the self-monitoring app reduced household food waste, although the magnitude of the effect appears to depend on baseline levels of food waste.

3.2 Effects of food waste measurement

A cloud-based automatic weighing system was used to measure food waste. In the questionnaire conducted after the intervention period, participants were asked to evaluate the influence of this measurement on their food waste–reduction behaviors using a four-point scale. Regarding food waste separation and the use of dedicated bin, 79% of the intervention group and 70% of the control group responded that these requirements "greatly influenced" or "somewhat influenced" their behavior.

To analyze the impact of food waste measurement on both groups, the frequency of food waste disposal among online panels (as described in Section 2.7) was measured using the same questions as for the control group. A two-way mixed ANOVA was conducted using the waste frequency data from the experimental control group and the online panels before and after the intervention period. The results showed no significant effects for leftovers from served meals ($F(1,146) = 0.012$, $p = .912$), leftovers from unserved meals ($F(1,142) = 0.340$, $p = .561$), unused fresh food ($F(1,143) = 1.238$, $p = .268$), or unused items ($F(1,147) = 0.143$, $p = .706$).

We also examined differences in disposal frequency between the intervention and control groups. A significant interaction effect was found for unused fresh food ($F(1,120) = 9.513$, $p = .003$). The mean difference in the simple main effect was −0.233 ($p < .05$) for the intervention group, indicating a significantly lower rate after the intervention, whereas the control group showed a significantly higher rate of 0.274 ($p < .05$).

3.3 Effects of the intervention on food waste reduction behaviors and their association with food waste reduction

3.3.1 Effects of the intervention on food waste reduction behaviors (H1)

First, descriptive statistics for the behavioral indicators during the baseline and intervention periods are presented in Appendix D. In the intervention group, mean scores increased from baseline to the intervention period for all behavioral indicators. In particular, "searching for foods to be used sooner" increased by 0.89, "inventory knowledge" by 0.81, and "preventing over-buying" by 0.67. As shown in Section 3.1, the amount of food waste in the intervention group decreased over the same period. In contrast, in the control group, only "inventory knowledge" and "prioritized food use" showed slight increases (both by 0.30), and no substantial changes were observed.

Correlations among the behavioral change scores are presented in Appendix E. The analysis showed that three behavioral changes were significantly associated with changes in food waste: "inventory knowledge" ($r = -.214$), "finishing meals" ($r = -.186$), and "preventing over-buying" ($r = -.232$). All three variables exhibited negative correlations, indicating that greater improvements in these behaviors were associated with larger reductions in food waste.

To examine the effects of the intervention on these behavioral indicators, GLMs were estimated (detailed results are presented in Appendix F). Table 3 reports the coefficients of the intervention group dummy variable and the bootstrap standard errors for the six behavioral indicators. As the six indicators belong to the same hypothesis family (H1a–H1f), p-values were adjusted using the

TABLE 3: Effects of the intervention on six behaviors (stratified bootstrap estimates with Holm–Bonferroni–adjusted p-values).

Variable	B	Bootstrap SE	Adjusted p value	95% CI
Searching for food that should be used sooner	0.672	0.156	.012	[0.374, 0.983]
Moving food that should be used sooner	0.681	0.176	.012	[0.345, 1.033]
Knowledge of the refrigerator inventory	0.437	0.150	.028	[0.145, 0.721]
Prioritized food use	-0.135	0.103	.194	[-0.333, 0.071]
Finishing meals	0.201	0.101	.128	[-0.004, 0.404]
Preventing over-buying	0.463	0.174	.027	[0.119, 0.798]

Note. B represents the unstandardized regression coefficients of the Intervention dummy. Standard errors were estimated using 1,000 stratified bootstrap resamples. P-values were adjusted using the Holm–Bonferroni procedure.

Holm–Bonferroni procedure (adjusted p-values; hereafter Adj-p). After adjustment, statistically significant intervention effects at the 5% level were observed for "searching for food" (Adj-p = .012), "moving food to a visible place" (Adj-p = .012), "inventory knowledge" (Adj-p = .028), and "preventing over-buying" (Adj-p = .027). In contrast, no significant effects were observed for "prioritized food use" (Adj-p = .194) or "finishing meals" (Adj-p = .128). These results indicate that among the H1 hypotheses, H1a, H1b, H1c, and H1e were supported, whereas H1d and H1f were not supported.

3.3.2 Effects of Behavioral Changes on Food Waste Reduction (H2)

Among the six behavioral indicators, three behaviors—"prioritized food use," "finishing meals," and "preventing over-buying"—were examined to assess whether changes in these behaviors were associated with reductions in food waste. GLMs were estimated using stratified bootstrap resampling (n = 1,000) (Table 4). The dependent variable was the change in food waste amount (intervention period – baseline period). Baseline food waste (mean-centered) and the change scores for the three behaviors were included as covariates, and the intervention group dummy variable was included as a between-subjects factor.

In the main-effects model without interaction terms (Table 4, Model 1), baseline food waste was statistically significant (B = −0.26, 95% CI [−0.487, −0.076], p = .012), indicating that households with higher baseline food waste tended to achieve greater reductions. The coefficient for the intervention group dummy variable was B = −85.82 (95% CI [−189.98, 22.64], p = .107), which was smaller in magnitude than in the model reported in Section 3.1 (B = −145.42, 95% CI [−265.56, −17.66], p = .036) and was no longer statistically significant.

Regarding the main effects of the behavioral variables, neither "prioritized food use" (B = 60.68, 95% CI [1.47, 127.44], p = .053) nor "finishing meals" (B = −81.91, 95% CI [−180.73, 12.54], p = .095) reached statistical significance. "Preventing over-buying" also showed no significant association with the change in food waste (B = 4.38, 95% CI [−33.01, 41.72], p = .821). Thus, none of the H2 hypotheses (H2a, H2b, and H2c) were supported in the confirmatory analysis.

Next, to explore whether the associations between behavioral changes and food waste reduction differed depending on baseline food waste levels, a model including interaction terms between baseline food waste and each behavioral change variable was estimated (Table 4, Model 2). No significant interaction was observed for "preventing over-buying" (B = 0.024, 95% CI [−0.139, 0.133], p = .673). A statistically significant interaction was observed for "prioritized food use" (B = 0.245, 95% CI [0.075, 0.449], p = .004). For "finishing meals," the estimated interaction term was negative, and the p-value indicated statistical significance (B = −0.177, 95% CI [−0.269, 0.034], p = .006); however, the 95% bootstrap confidence interval included zero.

Specifically, increases in "finishing meals" were associated with larger reductions in food waste among households with higher baseline food waste. In contrast, the positive coefficient for "prioritized food use", indicates that increases in this behavior were associated with increases in food waste among households with higher baseline food waste. Consistent with this finding, the simple correlation between the change scores of "prioritized food use" and food waste amount was also positive (r = .129; see Appendix E), although correlations between the corresponding non-change variables were negative (see Appendix G).

The coefficient of the intervention group dummy variable in Model 2 (Table 4) was B = −80.31 (95% CI [−184.73, 43.37], p = .158), which was similar in magnitude to that in the main-effects model (Model 1; B = −85.82) and remained statistically non-significant. Furthermore, the interaction between the intervention dummy variable and baseline food waste amount, which was significant in Section 3.1 (Table 2, Model 2; B = −0.55, 95% CI [−0.949, −0.083], p = .028), decreased substantially in magnitude in the present model (Table 4, Model 2; B = −0.269, 95% CI [−0.621, 0.166], p = .085) and was no longer statistically significant.

Overall, the results can be summarized as follows: among the H1 hypotheses, H1a, H1b, H1c, and H1e were supported, whereas H1d and H1f were not supported. None of the H2 hypotheses (H2a–H2c) were supported, while H3 was supported.

3.4 Evaluation of the self-monitoring app by participants

Participants in the intervention group (N = 63) were asked in the post-intervention questionnaire about their use and evaluations of the self-monitoring app. The questionnaire items and results are presented in Appendix C. Unless otherwise noted, the percentages reported below represent the combined proportion of the two most posi-

TABLE 4: Effects of the intervention and behavioral changes on change in household food waste (GLM with stratified bootstrap).

Dependent variable: Change in food waste (Intervention – Baseline)

Model 1. Main-Effects Model

Predictor	B	Bootstrap SE	95% CI	p
Intercept	-63.28	40.08	[-149.64, 9.59]	.127
Intervention group (1 = intervention)	-85.82	51.69	[-189.98, 22.64]	.107
Baseline food waste (centered)	-0.26	0.101	[-0.487, -0.076]	.012
Prioritized food use (change score)	60.68	31.74	[1.47, 127.44]	.053
Finishing meals (change score)	-81.91	49.47	[-180.73, 12.54]	.095
Preventing over-buying (change score)	4.38	19.63	[-33.01, 41.72]	.821

Model 2. Interaction Model

Predictor	B	Bootstrap SE	95% CI	p
Intercept	-80.22	39.47	[-163.85, -3.47]	.061
Intervention group (1 = intervention)	-80.31	57.52	[-184.73, 43.37]	.158
Baseline food waste (centered)	-0.179	0.139	[-0.501, 0.068]	.171
Prioritized food use (change score)	57.98	33.09	[-10.35, 126.30]	.070
Finishing meals (change score)	-63.3	38.3	[-117.60, 38.73]	.075
Preventing over-buying (change score)	4.86	22.06	[-41.78, 45.55]	.836
Intervention × Baseline food waste	-0.269	0.187	[-0.621, 0.166]	.085
Baseline × Prioritized food use	0.245	0.093	[0.075, 0.449]	.004
Baseline × Finishing meals	-0.177	0.077	[-0.269, 0.034]	.006
Baseline × Preventing over-buying	0.024	0.066	[-0.139, 0.133]	.673

Note. Estimates are based on 1,000 stratified bootstrap resamples (stratified by group). Two-tailed tests. Baseline variables were mean-centered.

tive response categories. For five-point scales, responses in the middle category were excluded from this calculation.

The vast majority of participants (94%) reported using the app five or more times per week. The perceived influence of the app on food waste reduction behaviors was measured using a four-point scale ("had no effect at all" to "had a significant effect"), and 75% of participants reported that the app had at least some influence.

The perceived influence of individual app features was measured using five-point scales ("had no effect at all" to "had a significant effect"). The combined proportion of the two highest categories was 78% for "Behavior checks," 67% for "Daily score," 60% for "Encouraging messages," 58% for "Leaderboard," and 58% for "Badges."

Perceptions related to usability and motivation were also measured using five-point scales. The highest proportion (combined top two categories) was observed for "Made me want to reduce food waste" (81%), followed by "Prompted me to take action" (73%) and "Motivated me" (71%). Regarding social and competitive aspects, 30% agreed that they "did not want to lose," 48% agreed that they "paid attention to the rankings," and 73% agreed that they "felt like working together with others."

Perceived burden was also measured using five-point scales, with 24% indicating that they "felt it was a hassle" and 32% indicating that they "felt it was a burden." In contrast, positive usability evaluations were high, with 90% indicating that the app was "easy," 83% that it was "easy to understand," and 79% that it was "easy to use."

All evaluations reported here reflect subjective assessments by participants in the intervention group at the time of the post-intervention questionnaire.

4. DISCUSSION

This study aimed to quantitatively examine the effects of an intervention on household food waste using a self-monitoring app with gamification features, based on objectively measured waste weight data from intervention and control groups, and to clarify its effects on related behaviors.

Six behavior-related indicators were analyzed: four direct target behaviors—"searching for food that should be used sooner," "moving such food to a visible place," "prioritized food use," and "finishing meals"—as well as two related behaviors, namely "inventory knowledge" (knowledge of food stocks and expiration dates in the refrigerator) and "preventing over-buying."

4.1 Impact of the intervention on target behaviors and effectiveness in reducing food waste

First, as shown in Section 3.2, although the measurement procedure had some psychological influence on participants, its impact on both the frequency and amount of food waste was limited. While the main effect of measurement was partially accounted for by comparing the intervention and control groups, the interaction between the weight measurement method and the intervention could not be addressed in this study. If an intervention group had also been assigned to the online panel participants, it would have been possible to examine the effect of measurement by comparing differences between the intervention groups; however, this was not done in the present study.

Next, as reported in Section 3.1, the intervention group showed a reduction of 190 g per household per week (a 45% decrease), and a further reduction of 130 g (32 percentage points) relative to the control group. Results from the general linear model further confirmed that the intervention using the self-monitoring app was associated with reduced food waste. In addition, the significant interaction with baseline food waste suggests that households with higher initial levels of food waste achieved greater reductions. This finding is consistent with the learning-based explanation proposed by Qi et al. (2023), which suggests that accumulating experience in recognizing one's past food waste through measurement and similar activities drives food waste reduction. However, because no significant association between baseline food waste and change was observed in the control group, despite the measurement system (including waste separation and the use of dedicated bins) being considered a form of self-monitoring, this learning mechanism does not appear to have operated in this context. It is likely that the combination of explicit behavioral guidance and motivational elements through gamification played a critical role in translating accumulated awareness into actual behavioral change. This interaction effect is also important from a policy perspective, as it indicates greater effectiveness among high-waste households and warrants further investigation.

Although strict comparisons are limited due to differences in measurement methods and baseline levels, the intervention effect observed in this study can be contextualized relative to previous studies based on the difference in reduction rates between the intervention and control groups (32 percentage points). This level is broadly comparable to the app-based intervention reported by Seta et al. (2025) (29%). However, the effect observed in this study is smaller than that reported for photo-based interventions (42%) and organizing tools (50%) in the same study. The effect is also comparable to that reported in Cooper et al. (2023) (27% and 33%), although their estimates were based on questionnaire data and therefore differ in measurement approach from the automated weighing system used in this study. For Pelt et al. (2020) and Soma et al. (2020), direct comparison is difficult because reduction rates relative to control groups were not reported. While these studies provide pre–post comparisons or post-intervention levels, differences in indicators limit their direct comparability. Taken together, the intervention effect observed in this study may be considered moderate within the existing literature, although careful interpretation is required given differences in measurement methods and baseline conditions.

Although a larger effect was expected for the gamified intervention in this study compared with Cooper et al. (2023; see Section 1.2.2), the observed effect was of a similar magnitude. One possible explanation is that Cooper et al.'s intervention combined not only motivational elements but also opportunity creation and ability support, as outlined in the MOA framework.

With respect to behavioral outcomes (Section 3.3.1), two of the four target behaviors ("search" and "move") showed significant effects. In addition, "inventory knowledge" and "preventing over-buying," which were conceptually linked to these behaviors, were also significantly affected. These findings suggest a behavioral pathway in which increased refrigerator organization enhances inventory knowledge, which in turn influences purchasing behavior and helps prevent over-buying.

In contrast, the remaining target behaviors, "prioritized food use" and "finishing meals," were not significant. These behaviors had relatively high baseline levels (mean = 4.08 for prioritized food use and 4.44 for finishing meals on a five-point scale), suggesting that ceiling effects may have limited observable changes.

The analysis examining the relationship between behavioral changes and reductions in food waste indicated that, although the behavioral changes themselves were not statistically significant, their inclusion attenuated the estimated intervention effect in the model, suggesting that behavioral changes may partially explain the intervention effect. For "finishing meals," the interaction with baseline food waste showed a statistically significant p-value, although the confidence interval included zero. This suggests that changes in behavior may have contributed to reductions in food waste, although the evidence should be interpreted with caution.

However, the results for "prioritized food use" were complex. Although this behavior is conceptually expected to reduce food waste, its change score was positively associated with changes in food waste, and its interaction with baseline waste was significant. One possible explanation is that the measure of prioritized food use reflects subjective evaluation conditional on recognizing food that should be consumed soon. As participants become more aware of such food through the intervention, their self-evaluation of prioritized food use may decrease even without an actual decline in behavior. At the same time, as more foods are identified as requiring prioritized food use, the amount of food that can be prevented from being discarded may increase, thereby contributing to reductions in food waste. This mechanism may account for the positive association observed between changes in prioritized food use and food waste. Furthermore, households with higher baseline food waste may become aware of more similar items through the intervention, potentially strengthening the interaction with baseline waste. Therefore, further refinement of the measurement scale and analytical approaches, including addressing potential ceiling effects, is required.

Regarding "preventing over-buying," although the intervention had a significant effect on this behavior, no direct association with food waste reduction was observed. While correlation analysis (Appendix D) suggested a relationship with food waste, the effect was not statistically significant in the multivariate model. This suggests that "preventing over-buying" may function in conjunction with other food management behaviors, and its independent effect on reducing food waste may be limited.

Taken together, these findings suggest that interventions combining structured behavioral guidance through self-monitoring with motivational design elements such as gamification may help reduce household food waste by promoting food management behaviors. However, their effects on the use-up and consumption stages were not clearly detected.

4.2 Effect of gamification on motivation

Based on the subjective evaluations of participants in the intervention group reported in Section 3.4, many participants were influenced by both self-monitoring through behavior recording and the app's gamified elements, which encouraged behavioral engagement and supported motivation.

In Soma et al. (2020), participants earned points by correctly answering quiz questions, and the value of coupons varied based on the number of points earned. Thus, the observed effects may have been influenced by financial incentives. In contrast, in the present study, all participants received the same reward regardless of their performance, and no monetary incentives were tied to points. Nevertheless, a substantial proportion of participants reported being motivated by points, suggesting that points served as an effective psychological reward. These results indicate that points earned through greater engagement in daily food waste reduction behaviors (linked to leaderboards and badges as part of a gamification mechanism) supported motivation, influenced food waste reduction behaviors, and may have contributed to reductions in food waste. The influence of the leaderboard was comparable to that of weekly ranking badges, whereas competitiveness-related indicators, presumably associated with the leaderboard, were somewhat lower. This finding may reflect that participants were less inclined to adopt a competitive mindset in the context of pro-environmental behavior, such as reducing food waste.

Notably, 73% of participants reported feeling they were "working together with others," despite having limited opportunities to directly recognize other participants beyond viewing the leaderboard on the home screen. Although the leaderboard was introduced primarily to enhance competitiveness, it may have fostered not only a competitive environment but also a sense of collaboration (Grech et al., 2024; Morschheuser et al., 2019; Riar et al., 2022). This interpretation is consistent with prior research suggesting that gamification can promote not only individual motivation but also collective and cooperative behavior, even among individuals who do not know each other, such as in online environments (Koivisto & Hamari, 2019).

If such characteristics can be effectively leveraged, gamified interventions may support both individual-level behavior change within households and collaborative behavior change at the group level, such as in communities or schools. Although the present study primarily examined intervention effects at the individual level, further research is needed to investigate how gamification functions within real social groups and to evaluate its effects on cooperative, group-based interventions.

Finally, because this study targeted individuals who voluntarily applied to participate as survey monitors, the sample cannot be considered representative of the general population in Japan. Participants may already have had a certain level of motivation to reduce food waste, which limits this study. Future research should examine the extent to which gamification-based motivation is effective among individuals without pre-existing motivation to reduce food waste, in contrast to the self-selected participants in the present study.

4.3 Effect of reducing participant burden

Reducing participant burden was key challenge addressed in this study, as 32% of participants reported that they found the intervention burdensome, and 24% reported that it was troublesome. In contrast, in the previous study, a majority (77%) of participants using a food management app reported that the intervention was troublesome. These results suggest that the present intervention substantially reduced perceived burden. In addition, the high ratings for "easy," "understandable," and "user-friendly" indicate that the intervention also helped reduce psychological burden.

From the perspective of dropout rate, an indirect indicator of participant burden, the present study demonstrated extremely low attrition, with only 4 out of 130 participants withdrawing, suggesting that participant burden was small. In Cooper et al. (2023), approximately 50% of participants dropped out during the five-week baseline period in one of the experiments, suggesting that participant burden may have been substantial. One possible explanation for this difference is that Cooper et al. (2023) required participants to complete specific tasks, such as preparing meals using "use-up" recipes on designated days. In contrast, the present study employed a simpler intervention based on daily behavior recording through the app. This simplified design may have reduced participant burden. Furthermore, incorporating gamification elements (e.g., points, badges, and leaderboards) into the self-monitoring process may have provided ongoing motivational incentives that sustained engagement, thereby contributing to the low dropout rate observed in this study.

It should also be noted that the recruitment criteria for this study required participants to be able to use a smartphone or PC to access the app. This requirement likely contributed to a higher proportion of younger participants and a lower proportion of older participants. As a result, the sample may have been biased toward individuals for whom the burden of using the app was relatively low. Therefore, the reported levels of perceived burden should be interpreted as subjective evaluations within a self-selected sample, and caution is needed when interpreting and generalizing the findings. However, it is worth noting that, in Seta et al. (2025), participants were also expected to use an app as part of the intervention. Therefore, the observed differences in perceived burden cannot be fully attributed to differences in recruitment conditions alone.

5. CONCLUSIONS

This study aimed to reduce household food waste by targeting four key behaviors: "searching for food that should be used sooner," "moving such food to a visible place," "prioritized use of food that should be used sooner," and "finishing meals." Building on Seta et al. (2025), which demonstrated the effectiveness of the first three behaviors, this study added "finishing meals" as an additional target behavior. To directly promote these behaviors while reducing the perceived burden of ICT tools and enhancing motivation, we designed and implemented a self-monitoring intervention using a gamified behavior-recording app. Food waste was objectively measured using a cloud-based weighing system. In addition to the four target behaviors, two complementary behavioral indicators, "inventory knowledge" and "preventing over-buying," were included to reflect the broader household food management process, resulting in six behaviors analyzed in this study.

The average weekly food waste per household decreased by 190 g (45%) in the intervention group, compared with 60 g (13%) in the control group, corresponding to a between-group difference of 32 percentage points. A GLM model with bootstrap inference, using the change in food waste as the dependent variable and baseline food waste as a covariate, showed that the intervention group achieved a significantly greater reduction in food waste than the control group ($B = -145.42$, 95% CI [-265.56, -17.66], $p = .036$).

Regarding behavioral outcomes, the intervention had significant effects on two target behaviors ("search" and "move"), as well as on "inventory knowledge" and "preventing over-buying," providing partial support for the H1 hypothesis set. In contrast, no significant effects were observed for the remaining target behaviors ("prioritized food use" and "finishing meals").

Further analysis examining the effects of behavioral changes in "prioritized food use," "finishing meals," and "preventing over-buying" on food waste reduction showed no significant associations in the main-effects model. However, exploratory analyses revealed significant interactions between baseline food waste and behavioral changes. Although the confidence interval for "finishing meals" included zero, this behavior was considered to have the potential to contribute to reductions in food waste. In contrast, for "prioritized food use," the observed relationship was not fully consistent with theoretical expectations, suggesting that the effects of this behavior may depend on its complex relationship with changes in awareness of food items that should be used sooner.

Subjective evaluations by participants in the intervention group indicated that daily self-monitoring increased awareness of food waste behaviors and that gamification elements enhanced motivation. In addition, perceived burden was lower than that reported in Seta et al. (2025). As these findings are exploratory, further confirmatory research is required.

The primary contribution of this study lies in the design and experimental validation of a self-monitoring intervention that directly promotes food waste reduction behaviors. In particular, this study proposes a ICT-based intervention framework that integrates gamification into a self-monitoring app, enhancing motivation while minimizing user burden. Furthermore, the finding that behavioral change can be promoted through psychological rewards without relying on financial incentives has practical implications for the design of sustainable interventions and policy implementation.

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