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Better social infrastructure matters: Impacts of perceptional and behavioral smartization on food-related household emissions and wastes

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ABSTRACT

Japan has been implementing policies to reduce greenhouse gas emissions (NDC goal) and food-related wastes (Food Recycling Act). However, these policies were mainly targeting commercial stakeholders instead of households. In this paper, we proposed a smart food transition framework with multiple dimensions, conducted a large sample size survey (5500 households in Japan) with consumer attitudes towards smart food services and smart eating habits, and investigated what may affect food-related household greenhouse gas emissions and food waste through a detailed assessment of both direct and indirect emissions. We found that, in the context of a better social infrastructure (e.g., better telecommunications infrastructure or higher penetration of SNS) where households can have a higher level of welfare and better access to smart food services, additional food waste would be generated, but not necessarily food-related greenhouse gas emissions. This is possible to be improved by perceptional changes and behavioral changes (e.g., more tolerance of using commercially prepared dishes, more willingness to use inventory management APPs). Our paper emphasized the importance of appropriate guidance in such perceptional changes and behavioral changes, together with detailed directions, for more decent household lives in the future of Japan.

1. Introduction

In October 2020, the then Prime Minister declared that Japan would become a carbon-neutral society by 2050 (Government of Japan, 2021). Among the global GHG emissions, 72% of them are consumption-induced emissions (Hertwich and Peters, 2009). This calls for tracking such emissions induced by final users. Also, according to Hertwich and Peters (2009), food, residence, and mobility are the three major sectors in GHG emissions from household consumption. The latter two occupy a larger share in developed countries. However, in Japan, one of the most developed countries, share of GHG emissions from residences and mobility has been on a downward trend or decreasing in the last 10 years (Kanemoto et al., 2020; Long et al., 2022; Nakano and Washizu, 2020). Carbon footprints from the consumption of food are also an important issue in Japan.

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According to the Food and Agriculture Organization (FAO, 2019), approximately 14% of the world's food is wasted before it reaches stores. Also, according to the UNEP (2023), an additional 17% of the world's food is wasted at the retail and consumption stages (particularly in households). Addressing food loss and waste offers a triple-win opportunity for climate change mitigation and food security and sustainable agricultural food systems. SDG 12.3 sets the goal of reducing food loss (from supply chain to retail) and halving per capita global food waste at the retail and consumption level (from retail to final consumers).

However, in Japan, the definitions of food waste and loss are slightly different. "Food waste" in Japan is defined in the "Act on Promotion of Recycling, etc. of Food Circulating Resources" in the Food Recycling Act (MAFF, 2019), refering to "food that is discarded after it has been made edible or without being made edible" and "food manufacturing, processing, etc. or products obtained as by-products in the process of cooking that cannot be used for human consumption." Specifically, in the act, "useful food waste and the like" denotes "food recyclable resources." The purpose of the Food Recycling Act is to establish policies and numerical targets for recycling unknown "food circulation resources." The term "food loss" is used in the "Act on Promotion of Food Loss Reduction" (MOE, 2019) as follows: "Reducing food loss" refers to social efforts to prevent food that can be discarded from being wasted. In other words, "food loss" refers to food waste that is still edible but being thrown away. There is a distinction between business- and household-related food waste and loss: the former is under the jurisdiction of the Ministry of Agriculture, Forestry, and Fisheries (MAFF), and the latter is under the Ministry of the Environment (MOE) which is what we are using in this paper.

Therefore, in Japan, to achieve SDG 12.3 aiming to halve food loss by 2030, the national goal will be stipulated by the Food Recycling Law for business-related food loss and by the "Fourth Basic Plan for Establishing a Recycling-based Society (2018)" for addressing household food loss. The amount of food loss in 2000 was 5.47 million tons from business sources (MAFF) and 4.33 million tons from households (MOE), with the target values for 2030 set as 2.73 and 2.16 million tons, respectively. Regarding consumer behavior, a goal has been set to increase the percentage of consumers who are aware of the food waste problem and actively participate in reducing it to 80%. The food loss in the fiscal year 2020 was 5.22 million tons (with 2.75 million tons of household food loss and 2.47 million tons of household food loss).

To accelerate the achievement of such a national goal, policies have been implemented to reduce food waste, particularly food loss, using digital technologies (e.g., Information and Communication Technology (ICT) and Artificial Intelligence (AI) that help prevent food loss). However, these policies are mainly targeting business-related food loss or greenhouse gas emissions while not paying enough attention to households (Long et al., 2021a, 2021b; Shigetomi et al., 2021; Tsuchiya et al., 2021). To investigate the mechanism of household smartization and its possible impact on food-related emissions and wastes, we conducted a large-scale survey covering 5500 households in Japan, from both highly urbanized and other regions.

Previous literature that estimates a national level of household carbon footprints contains detailed accounting for those related to food (Eisenack and Roggero, 2022; Long et al., 2021a, 2021b), including both direct emissions from cooking and indirect emissions from the supply chain of ingredients; and even to temporal distribution to capture the lifestyle patterns of household emissions (Huang et al., 2023). Such accounting is based on household expenses (usually derived from national-level family income and expenditure surveys, e.g., FIES in Japan). We adopted a similar expense-based approach so that all indirect emissions from 20+ categories of ingredients can be included. We further took advantage of our large sample size, so that the feature-rich (features of households containing their attitudes towards smart food services and smart eating habits) and bottom-up results can be matched back with the national level household emissions. The sampling of metropolitan cities (district-level) and other prefectures also allows us to better understand the differences between urban household behaviors and the others, as well as the impact of policies implemented in pilot cities to promote household emission reduction and food loss reduction.

We proposed a new framework to analyze such a transition (smartization) towards using smart food services and having smarter eating habits. The framework is based on the home production function total home production (maximizing the utility of the meal, quantified by the home production determined by cooking effort minus total actual cooking effort determined by the cooking efforts and usage intensity of convenience food, applied in Canelas et al., 2019; Etilé and Plessz, 2018; Kohara and Kamiya, 2016). Considering the incompatible relation between cooking effort and usage intensity of convenience food, we separated the smartization into three dimensions: technological dimension (reduce actual cooking effort by using more convenience food), behavioral dimension (with the same usage intensity of convenience food, having more utility by shifting preference to using more smart food services), and perceptional dimension (with the same cooking effort, shifting to being more willing to use more convenience food). We then introduced the forth social dimension to investigate the impact of the overall social environment. We used the different levels of social infrastructure conditions in highly urbanized regions and other regions and then analyzed how all different dimensions of smartization may accelerate the reduction of household emissions and food loss. In summary, through the smart food transition framework with multiple dimensions, this paper can provide important references to perceptional and behavioral shift instruction for emission and food loss reduction in households.

2. Methodology

2.1. Survey

We conducted a questionnaire survey to collect information from 5500 households in Japan, from both highly urbanized and other regions, regarding each dimension of smart food services and eating habits. The survey was conducted from November 11 to December 6, 2021 by Rakuten Insight Inc. The sampling process includes the division of subgroups based on the demographic and geographic characteristics (i.e., gender, age, sub-regions, family type) in Japan and the weight adjustment of subgroups to align with the baseline population distribution (Japan 2015 population census). This adjustment helps to ensure that the survey results are representative of

Japan's entire population of interest, including highly urbanized regions and others. Table 1 presents a breakdown of the 5500 households.

The survey questions include, the number of people having dinners in 3 days, the number of dishes in those dinners, the number of all ingredients that those dishes used (22 categories) and their expenditure, the heating time (microwave, gas, IH), wastes (packaging materials, food loss, and kitchen waste), the attitudes towards smart food services and smart eating habits (13 questions), and acceptance to PCs and smartphones (10 questions). Demographic features such as age of the householder, annual income, family type, and living regions are also collected.

Data cleaning is conducted by removing the unreasonable responses (e.g., 348 min used for using microwave) by thresholds (e.g., top 0.1%). For procedures see Table S1. After data cleaning, we were left with 13,750 responses from 4869 households.

2.2. Household carbon footprints

For each household, we evaluated both the CO_2 emissions from cooking and the total CO_2 emissions embodied in the supply chain of food ingredients.

The CO_2 emissions from cooking using the qth type of cooking energy source (3 in all, microwave, gas stove, IH stove) for each person in the pth household, $cfcook_{p,q}$, is formulated as

$$cfcook_{p,q} = power_q \bullet \frac{t_{p,q}}{n_p} \bullet eincook_q, \tag{1}$$

where $power_q$ refers to the average power of the qth type of cooking appliance (unit: kW, or MJ/h converted to kW), $t_{p,q}$ refers to the cooking time using the qth type of cooking appliance in the pth household (unit: hour), n_p refers to the number of family members in the pth household, and $eincook_q$ refers to CO_2 emission intensity of the qth type of cooking appliance (unit: kg-CO_2/kWh).

The total CO_2 emissions embodied in the supply chain of food ingredients are calculated based on the expenditure data collected from our survey and the environmentally extended input-output table. The expenditure of the kth category of ingredient for each person in the nth day in the pth household, $expen_{k,n,p}$, is formulated as

$$expen_{k,n,p} = \frac{e_{n,p}}{n_p} \bullet \frac{pri_k \bullet x_{k,n,p}}{\sum_k pri_k \bullet x_{k,n,p}}, \tag{2}$$

where $e_{n,p}$ refers to the expenditure of the overall expenditure of one dinner in the nth day in the pth household, n_p refers to the number of family members in the pth household, $x_{k,n,p}$ refers to the number of the kth category of ingredient used in one dinner on the nth day in the pth household, and pri_k refers to its price indicator, namely the price indicator of the kth category of ingredient which is used in that one dinner in the nth day in the pth household. The price indicators are calculated as the weights of 22 categories in the overall household expenditure, matched by the categorization in the 2020 national survey (the Family Income and Expenditure Survey in Japan).

Based on the expenditure ($expen_{k,n,p}$), the total CO_2 emissions embodied in the supply chain of the kth category of ingredient in the

Table 1
Sample structure and valid response after data cleaning.

Sample structure	Household type 1	Household type 2	Household type 3	Household type 4
	Single (male)	Single (female)	Couple only	Couple and children
Tokyo and other metropolitan cities (2247 households)				
20–39 years old	183	183	92	138
40–64 years old	183	92	138	672
over 65 years	92	183	229	62
Total	458	458	459	872
Others (3253 households)				
20–39 years old	229	92	92	367
40–64 years old	275	138	506	474
over 65 years	183	321	510	66
Total	687	551	1108	907
Valid responses after data cleaning	Household type 1 Single (male)	Household type 2 Single (female)	Household type 3 Couple only	Household type 4 Couple and children
Tokyo and other metropolitan cities (1982 households)				
20–39 years old	146	171	83	124
40–64 years old	149	81	129	6 01
over 65 years	76	161	2 06	55
Total	371	413	418	780
Others (2887 households)				
20–39 years old	192	86	87	343
40–64 years old	223	117	40	428
over 65 years	153	288	450	60
Total	568	491	997	831

nth day in the pth household, $cf_{k,n,p}$, is formulated as

$$\mathbf{ci} = \mathbf{ci}^{\mathrm{d}}(\mathbf{I} - \mathbf{A})^{-1}, \tag{3}$$

$$cf_{k,n,p} = ci_k \bullet expen_{k,n,p}, \tag{4}$$

where ci_k refers to the total emission intensity of the kth category of ingredients. It is an element from the total emission intensity vector $\mathbf{ci}$, which is calculated by the direct emission intensity $\mathbf{ci}^{\mathrm{d}}$ and the Leontief inverse matrix $(\mathbf{I} - \mathbf{A})^{-1}$, so that all the induced emissions in the food production supply chain can be covered.

2.3. Wastes

The food-related waste is self-reported data collected from our survey. In several most recent household survey implementations (Bilska et al., 2024; Eičaitė and Baležentis, 2024), the food-related waste data is collected in weight (grams) and in category. Considering the easiness for Japanese respondents to report, we asked about the amount of 3 types of food-related waste (packaging materials, food loss, and kitchen waste) generated per meal on a 6-level scale (more than one large-size plastic bag, one large-size plastic bag, half of one large-size plastic bag, one middle-size plastic bag, half of one middle-size plastic bag, almost no waste). The food-related waste of the hth type of waste from each person in the pth household is formulated as

$$waste_{h,p} = \frac{w_{h,p} \bullet cov_h}{n_p}, \tag{5}$$

where $w_{h,p}$ refers to the food-related waste of the hth type of waste in the pth household on a 6-level scale, cov_h refers to the converters changing 6-level scale reports of wastes (in bag size) to weight results (in grams, details of the converter see Table S3), and n_p refers to the number of family members in the pth household.

2.4. Social drivers

The social drivers to accelerate smartization (the overall social environment due to the urbanization level, e.g., the penetration of SNS and the telecommunications infrastructure) are analyzed by investigating the differences across highly urbanized regions and others.

Regarding the highly urbanized regions, we would test the following different scopes, Tokyo 23 wards, Tokyo 23 wards and government ordinance-designated cities in the 4 Tokyo metropolitan area prefectures, Tokyo 23 wards and all government ordinance-designated cities, and 4 Tokyo metropolitan area prefectures.

2.5. Technological drivers

The technological drivers to accelerate smartization is analyzed by investigating the level of using convenience food (those that would make the cooking effortless). We use indicator usage intensity of convenience food, which is also used in Nakano and Washizu (2020), to quantify such technological drivers. Next, the usage intensity of convenience food for dinner on the nth day in the pth household, $inf_{n,p}$, is formulated as

$$inf_{n,p} = \sum_k prox_k \bullet \frac{x_{k,n,p}}{\sum_k x_{k,n,p}}, \tag{5}$$

where $x_{k,n,p}$ refers to the number of the kth category of ingredient used in one dinner on the nth day in the pth household, and $prox_k$ refers to the proximity score of the kth category of ingredients. The proximity score (a virtual distance to the dining table) is defined such that it was high for ingredients that were processed to save the effort of cooking at home and low for ingredients that were not. To create this index, we borrowed the classification of fresh and processed foods in the Japanese Agricultural Standards Act (JAS Act) and the NOVA classification (Monteiro et al., 2016). The NOVA classification is internationally recognized as a food classification system that is based on the degree and purpose of processing applied to foods. Based on the act and classification, we created the following 8-level index, as shown in Table S2.

2.6. Perceptional drivers

The survey questions to collect the perceptional information include:

- Would you like to use a cooking device that uses AI to learn your preferences, suggest menus, and then, prepare the dishes by considering the ingredients? (willingness to use AI, *use_ai*)
- By registering long-term shelf-stable ingredients at home on the app, the AI will tell you the expiration date of the registered ingredients and suggest recommended recipes, using the ingredients that are nearing their expiration date. Would you like to use that APP? (willingness to use inventory management APP, *use_app*)

- Would you like to use a food-sharing and matching service that aims to reduce food waste by connecting consumers with restaurants that provide products that are at risk of being discarded due to customer cancellations? (willingness to use matching services, *use_matching*)
- If there was a shopping site for food and daily necessities that were discarded due to impending expiration dates, packaging changes, limited-time promotions, etc., would you want to use it? (willingness to use services managing food close to expiry dates, *close_expiry*)
- Do you feel unsatisfied if you use meal kits or other convenient ingredients to save time on meal preparation? (tolerance of using commercial meal kits, *use_mealkit*)
- Do you feel unsatisfied if you place store-bought prepared foods on the table to save yourself the trouble of preparing meals? (tolerance of using commercially prepared dishes, *use_convf*)
- If there was a service that suggested a meal plan and delivered the necessary ingredients, would you want to use it? (willingness to use ingredient deliveries, *use_delivery*)
- If there was a service that introduced you to people who could help you with cooking or shopping, would you use it? (willingness to use shopping-helper service, *shop_helper*)
- If there is a supermarket that is making efforts to reduce food waste using information and communication technology (e.g., smartphone apps and the Internet), would you want to actively use it, even if it does not have the lowest price? (willingness to support the stores that make efforts to reduce food loss, *for_smartmarket*)

2.7. Behavioral drivers

The behavioral drivers to accelerate smartization are analyzed by investigating the cooking effort, inventory check for food loss reduction, food preservation innovations to reduce food loss, and using mail order and home delivery of foodstuffs.

Table 2
List of variables and parameters.

Counter	Definition	Data source
k	Counter of ingredient category (22 in all)	
n	Counter of the days (2 in all)	
p	Counter of households (5500 in all)	
q	Counter of cooking appliance type (3 in all)	
h	Counter of the food-related waste type (3 in all)	

From survey	Definition	Data source
$e_{n,p}$	Expenditure of one dinner in the nth day in the pth household	
$t_{p,q}$	Cooking time using the qth type of cooking appliance in the pth household	
n_p	Number of family members in the pth household	
$x_{k,n,p}$	Number of the kth category of ingredient used in one dinner in the nth day in the pth household	
$d_{n,p}$	Number of dishes for the dinner on the nth day in the pth household	
$w_{h,p}$	Food-related waste of the hth type of waste in the pth household	

Other parameters	Definition	Data source
$power_q$	Average power of the qth type of cooking appliance For microwave, 1.3 kW For gas stove, 45 MJ/m^3 For IH stove, 0.7 kW	 Looop electricity (2023) Average output, Goodfellows, 2023 Panasonic models typical
$eincook_q$	CO_2 emission intensity of the qth type of cooking appliance For microwave, 0.457 kg-CO_2/kWh For gas stove, 3.6 MJ/h, 2.21 kg-CO_2/m^3 For IH stove, 0.457 kg-CO_2/kWh	 MOE (2023) TokyoGas, 2023 MOE (2023)
pri_k	Price indicator (weight) of the kth category of ingredient	Family Income and Expenditure Survey (FIES, 2015); parameter see Table S2)
ci_k, or $\mathbf{ci}^{\mathrm{d}}(\mathbf{I}-\mathbf{A})^{-1}$	Overall emission intensity	Embodied Energy and Emission Intensity Data for Japan Using Input-Output Tables (3EID, 2015); parameter see Table S2
cov_h	Converters changing 6-level scale reports of wastes (in bag size) to weight results (in grams)	Standardized bag size, parameter see Table S3
$prox_k$	Proximity score of the kth category of ingredient	Japanese Agricultural Standards Act and the NOVA classification, parameter see Table S2

Similar to Nakano and Washizu (2020), we quantified the cooking effort with the number of dishes and ingredients in each dinner. Also, cooking labor differs from normal labor. It does not necessarily involve a sense of negative burden. Sometimes, cooks enjoy cooking and each cook has a different sense of value regarding the cooking effort (Casini et al., 2019). The cooking effort for the dinner on in the nth day in the pth household, $ine_{n,p}$, is formulated as

$$ine_{n,p} = d_{n,p} \bullet \sum_{k} x_{k,n,p}, \tag{7}$$

where $d_{n,p}$ refers to the number of dishes for dinner on the nth day in the pth household, and $x_{k,n,p}$ refers to the number of the kth category of ingredient used in that dinner on the nth day in the pth household.

The survey questions to collect the behavioral information include:

- Do you check the inventory in your refrigerator and pantry before shopping for ingredients to reduce food loss? (inventory check for food loss reduction, *avoid_loss*)
- To reduce food waste, do you take measures such as freezing the food in small portions to preserve and use later? (food preservation innovations to reduce food loss, *process*)
- Do you purchase ingredients and meals online instead of going directly to stores? (using mail order and home delivery of foodstuffs, *remote_order*)

2.8. Counters, parameters, variables, and data sources

Table 2 lists the counters, parameters, variables, and data sources.

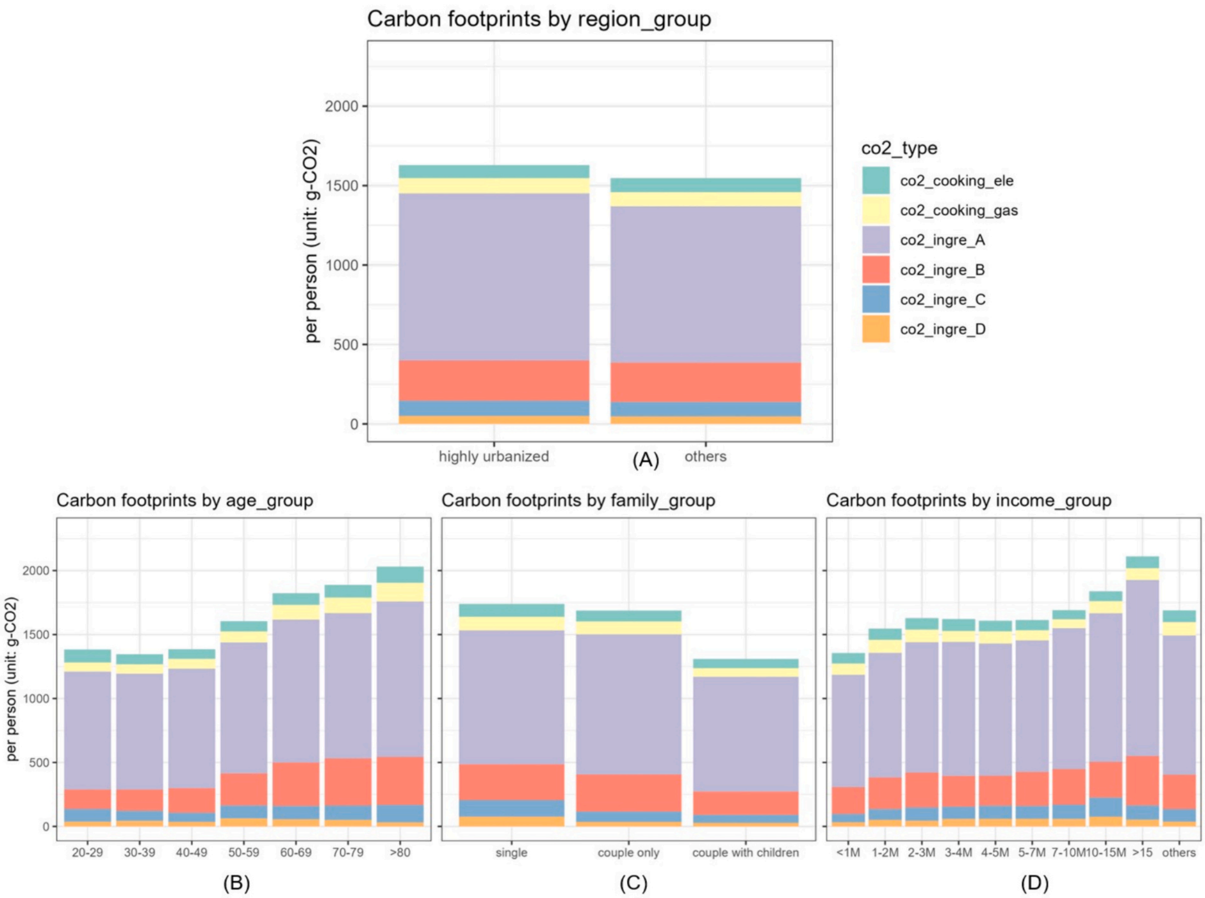

Fig. 1. Food-related household carbon footprints by region (A), age groups (B), family types (C), and income levels (D).
Ingredient type co2_ingre_A, co2_ingre_B, co2_ingre_C, co2_ingre_D see Table S2. Similar to the proximity score, ingredient type A includes the ingredients that would require more cooking effort, and ingredient type D includes the ingredients that would require less cooking effort. co2_cooking_ele includes the carbon footprints from using cooking appliances such as IH stoves and microwave ovens. co2_cooking_gas includes the carbon footprints from using cooking appliance gas stoves.

3. Results

3.1. Food-related household carbon footprints in highly urbanized and other regions

The result of food-related household carbon footprints in highly urbanized regions and other regions is shown in Fig. 1, together with the food-related household carbon footprints by other demographic features.

The average food-related household carbon footprints in highly urbanized regions are higher than those in other regions, especially the carbon footprints from using ingredients with lower convenience levels (requiring more cooking efforts). As the household carbon footprints from ingredients in this paper are determined by the total expenditure on different ingredients and their emission intensity covering all the supply chains, the difference between carbon footprints in highly urbanized regions and other regions can be a result of the difference in the price level. However, after we checked the average value of expenditure per person per meal by prefecture, the total expenditure on food was not particularly high in highly urbanized regions. Such differences should be considered as a result of the difference in eating habits (the structure of ingredients rather than the total amount) between highly urbanized regions and others. The transition to smart eating habits in the context of a better social environment (with better telecommunications infrastructure or higher penetration of SNS) may increase the average value of carbon footprints. A further breakdown of drivers, namely the contribution of perceptional changes and behavioral changes to possibly bring down the increasing carbon footprints, see section 3.3.

For other features, the average food-related household carbon footprints in generations over 50 years old would be higher than that for younger generations (older cooks spend more on ingredients). The average cost of ingredients C and D (higher proximity score, requiring less cooking effort) per meal per person would be lower in older households. The share of it in the age group 20–40, 40–65, 65+ would be 16.8%, 14.8%, and 14.3%, respectively. The younger generation portrayed a higher proportion of expenditure on convenience foods. Households in their 30s generate the least greenhouse gas emissions. Also, the average food-related household carbon footprints per person were lower in single families and higher in families with a couple and children; lower in lower-income families (less than 2 million JPY per year) and higher in higher-income families (more than 7 million JPY per year), but no significant difference in middle-income families.

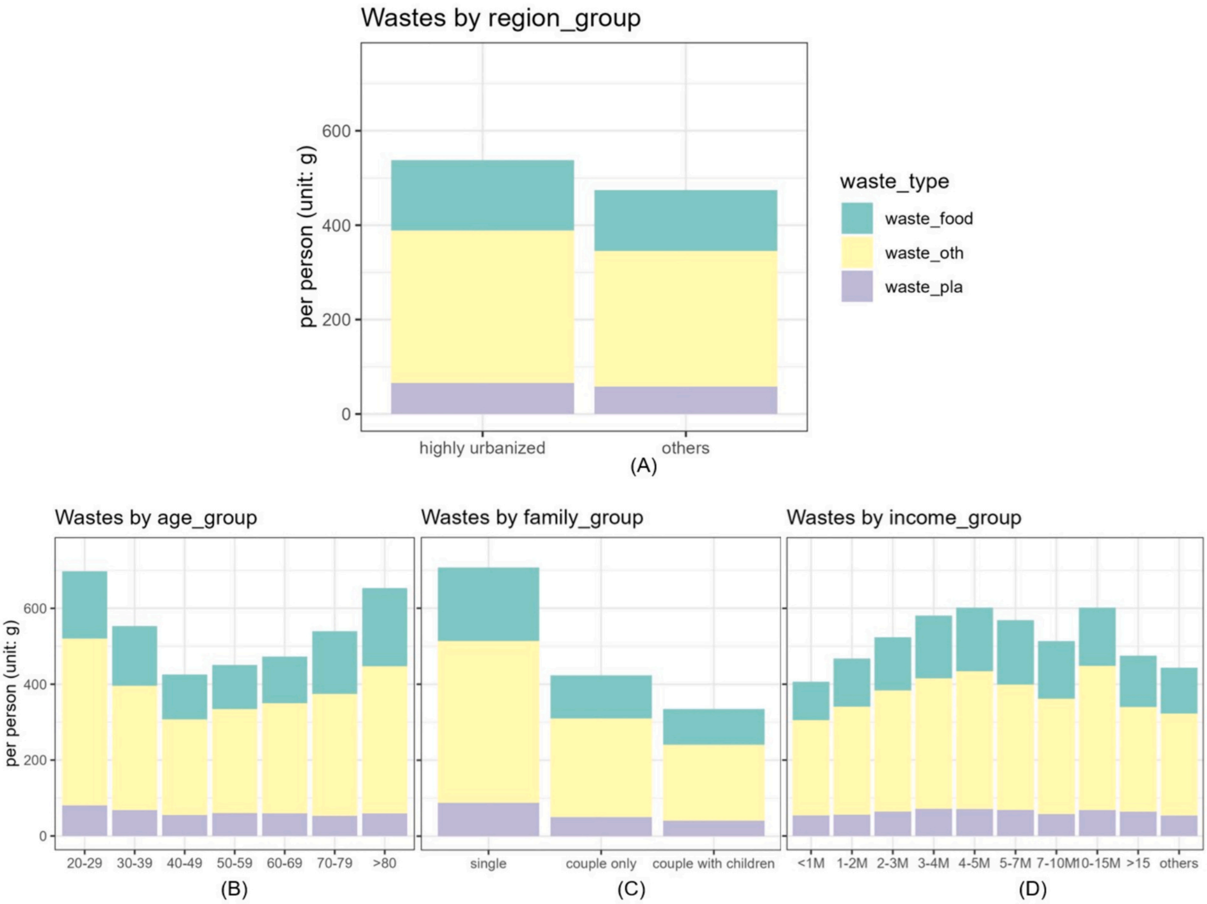

Fig. 2. Food-related waste by region (A), age groups (B), family types (C), and income levels (D).
waste_food refers to the food loss, waste_pla refers to the packaging materials, waste_oth refers to the rest of kitchen waste.

3.2. Food-related wastes in highly urbanized and other regions

The result of food-related wastes from households in highly urbanized regions and other regions is shown in Fig. 2, together with the food-related wastes from households by other demographic features.

The average amount of food-related waste from households in highly urbanized regions is higher than those in other regions, with slight differences in food loss and packaging materials, but a gap in the overall amount. The transition to smart eating habits or better access to smart food services in the context of a better social environment (with better telecommunications infrastructure or higher penetration of SNS) may increase the average value of food-related wastes. A further breakdown of drivers, namely the contribution of perceptional changes and behavioral changes to possibly bring down the increasing food-related wastes, see section 3.3.

For other features, different from the distribution of the average food-related household carbon footprints in generations, the average food-related waste in households would be higher in both younger (20–40 years old) and older families (over 65 years old), but lower in the middle-aged households (40–60 years old). Also, as a result of the difference in using convenience food, the average food-related household carbon footprints per person were higher in singer families and lower in families with a couple and children. Moreover, different from the distribution of the average food-related household carbon footprints in income levels, middle-income families (3 million to 7 million JPY per year) and extremely high-income families (more than 15 million JPY per year) would generate most food-related waste.

3.3. Perception and behavior differences across regions

The perception of using smart food services (the first 9 factors) and the actual behavior (the last 3 factors) in both highly urbanized regions and other regions are shown in Fig. 3.

We observed that smart food services offering direct benefits to households received higher scores in terms of willingness to use (i.e., happy to use meal kits and commercially prepared dishes, more willing to use delivery services, and more willing to use services suggested by their shopping helpers). Conversely, those services that households do not directly benefit from (i.e., using APPs to gain helpful information, receive menu suggestions, or track their inventories to avoid food loss) received lower scores in the willingness to use. In between, smart cooking devices equipped with AI (directly reducing cooking effort and indirectly providing information services) do not look attractive to households. Similarly, households showed limited enthusiasm for a shopping site of products close to

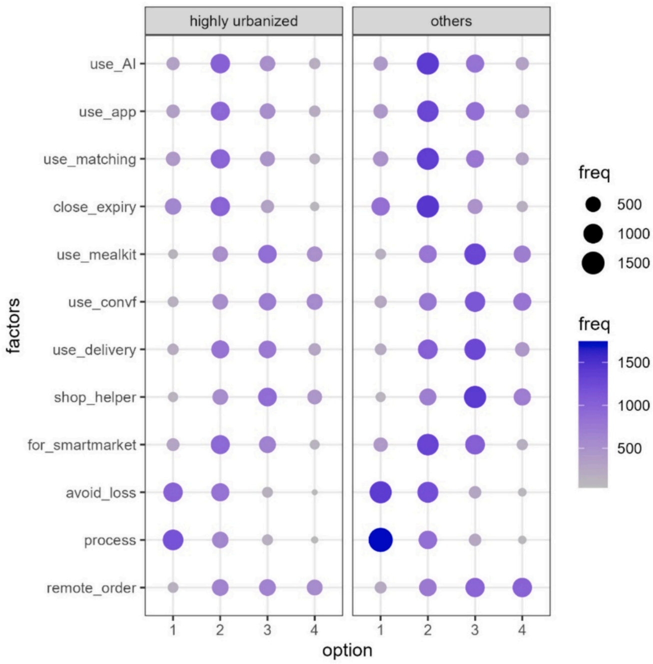

Fig. 3. The frequency of perception and the actual behavior survey questions in both highly urbanized regions.
For perception-dimension questions (the first 9 factors), the higher score in 1–4 the more agreement to try smart food services (the scores of the 2 factors asking tolerance rather than willingness have been reversed); for behavior questions, the higher score in 1–4 the higher frequency; use_ai: willingness to use AI; use_app: willingness to use inventory management app; use_matching: willingness to use matching services; close_expiry: willingness to use services managing food close to expiry dates; use_mealkit: tolerance of using commercial meal kits; use_convf: tolerance of using commercially prepared dishes; use_delivery: willingness to use ingredient deliveries; shop_helper: willingness to use shopping-helper service; for_smartmarket: willingness to support the stores that take efforts to reduce food loss; ine: cooking effort; avoid_loss: inventory check for food loss reduction; process: food preservation innovations to reduce food loss; remote_order: using mail order and home delivery of foodstuffs.

expiry (directly selling products and indirectly providing sales information).

Compared to the perception of using smart food services, the actual behaviors were worse. The cooks of the households are not putting additional effort in order to avoid food loss (either by checking the stock in the refrigerator before shopping or by preserving food by freezing in small portions so that they can be easily used up) based on our self-reported results. This also indicates the difficulties in converting perceptional changes to behavior changes.

It can also be observed that the differences are small between highly urbanized regions and the other regions regarding the perceptional and behavioral features. We conducted the regression analysis in Section 3.4 to further reveal their impacts.

3.4. Regression results: Impacts of technological, perceptional, and behavioral changes on food-related household carbon footprints and wastes

We tested the following different scopes to identify the highly urbanized regions in Japan, including Tokyo 23 wards, Tokyo 23 wards and government ordinance-designated cities in the 4 Tokyo metropolitan area prefectures, Tokyo 23 wards and all government ordinance-designated cities, and 4 Tokyo metropolitan area prefectures.

The results show that only the scope of Tokyo 23 wards would show statistically significant differences in the average value of technology level (namely, the usage intensity of convenience food). Thus, all results of highly urbanized regions in the following refer to the results of Tokyo 23 wards.

Regression analysis was performed to investigate the impacts of technological, perceptional, and behavioral changes on food-related household carbon footprints and wastes. The dependent variables include food-related household carbon footprints (from cooking and ingredients, calculated by section 2.2) and food-related wastes from households (food loss, kitchen waste, and plastic materials, calculated by section 2.3). The independent variables include the social (section 2.4), technological (section 2.5), perceptional (section 2.6), and behavioral drivers (section 2.7). We also included the interaction terms of social and perceptional dimensions. The regression results are shown in Table 3 and Table 4. Details of key indicators of highly urbanized regions and other regions are listed in Table S4.

We investigated the impacts of smart technology, social environment, perception, and behavior on household emissions on both

Table 3

Regression result: the impacts of smart technology, social environment, perception, and behavior on household emissions.

		Carbon footprint		Carbon footprint$\vert$cooking	
single person household		−5.59		0.08	**
household with only husband and wife		−23.89	**	0.03	**
age (under 40 years)		27.91	**	−0.01	**
age (over 65 years)		−40.47	**	0.02	**
woman		−48.97	**	0.08	**
Technological dimension					**
	usage intensity of convenience food	−130.38	**	−0.02	**
Social dimension					
	highly urbanized regions	−12.43		0.01	
Perceptional dimension					
	willingness to use AI cooking devices	−11.07		−0.01	*
	willingness to use inventory management APP	10.47		0.01	*
	willingness to use matching services	−11.32		0.01	**
	willingness to use services managing food close to expiry dates	−21.41	**	0.00	
	tolerance of using commercial meal kits	−3.87		0.00	
	tolerance of using commercially prepared dishes	14.13	*	0.00	
	willingness to use ingredient deliveries	12.85	*	0.00	
	willingness to use shopping-helper service	28.21	**	0.00	
	willingness to support the stores that take efforts to reduce food loss	9.84		0.00	
Social x Perceptional dimension					
Highly urbanized region ×	willingness to use AI cooking devices	14.91		0.03	**
	willingness to use inventory management APP	34.10		0.01	
	willingness to use matching services	−28.84		−0.03	**
	willingness to use services managing food close to expiry dates	41.73	*	0.01	
	tolerance of using commercial meal kits	−0.32		0.00	
	tolerance of using commercially prepared dishes	−35.58	*	0.01	
	willingness to use ingredient deliveries	0.18		−0.03	**
	willingness to use shopping-helper service	8.84		−0.01	
	willingness to support the stores that take efforts to reduce food loss	−11.13		0.00	
Behavioral dimension					
	cooking effort	−1.86	**	0.00	**
	inventory check for food loss reduction	−24.34	**	0.01	**
	food preservation innovations to reduce food loss	−35.14	**	0.01	
	using mail order and home delivery of foodstuffs	6.40		0.00	
	Number of observations	13,750		13,750	
	adj.R2	0.886		0.139	

*represents the 10% significance level, and **does the 5% significance level.

food-related household emissions (with the highest adj. $R^2 = 0.886$) and its sub-category emissions from cooking. The impact of the technological driver was significantly negative. Using more convenience food may reduce food-related household emissions, both from decarbonizing the food-related supply chain and from shortening the cooking time. In contrast, the impact of the social driver was not statistically significant, indicating that households in highly urbanized regions do not necessarily generate more (or less) food-related emissions.

Perceptional changes such as being more willing to use services managing food close to expiry dates can also be good drivers to reduce food-related household emissions. However, households that are happy to use commercially prepared dishes, ingredient deliveries, and shopping helper services are the ones that generate more carbon footprints. The features may change if considering the impact of both social and personal dimensions, indicating that, in the smartization system transition towards a social environment with better telecommunication access, the overall household emission level may increase, and the probability of mitigating such household emissions by perceptional changes would be low.

Behavioral changes, on the other hand, may significantly reduce household emissions. Households that frequently freeze their food in small portions to preserve and use later, check inventories before going shopping, and put in more cooking effort, generate less overall carbon footprints. It is achieved not through reducing the heating time (reducing the emissions from cooking) but through cutting the unnecessary consumption of food products and services (reducing the emissions embodied in the food supply chain).

We then investigated the impacts of smart technology, social environment, perception, and behavior on household emissions of all three types of food waste. The impact of the technological driver was significantly positive in two types. While using more convenience food may reduce household carbon footprint, it will increase both food loss and plastic wrapping materials. The transition to smart eating habits with lower cooking efforts would reduce food-related household carbon emissions and kitchen waste but increase food loss and plastic waste. This suggests that it is essential to adjust the amount per serving of convenience foods and the appropriate packaging container size. Similarly, the impact of the social driver was significantly positive in both food loss and plastic wrapping materials, indicating that households in highly urbanized regions may generate more food loss and plastic wrapping materials.

Perceptional changes such as being more willing to use services managing food close to expiry dates and more willing to use meal kits can be good drivers to reduce food waste. However, households that reported a higher level of willingness to use inventory management APPs, to use shopping-helper services, and to support the stores that make efforts to reduce food loss are actually the ones

Table 4
Regression result: the impacts of smart technology, social environment, perception, and behavior on household food wastes.

		food loss		plastic wrappings		kitchen waste	
single person household		78.27	**	46.35	**	223.55	**
household with only husband and wife		22.10	**	14.50	**	73.41	**
age (under 40 years)		24.94	**	5.51	**	56.79	**
age (over 65 years)		15.50	**	−13.30	**	−10.91	
woman		−16.16	**	−3.76	**	−17.84	**
Technological dimension							
	usage intensity of convenience food	10.43	**	1.99	**	−6.90	**
Social dimension							
	highly urbanized regions	73.47	**	12.31	**	113.47	**
Perceptional dimension							
	willingness to use AI cooking devices	−4.16		2.67		223.55	**
	willingness to use inventory management APP	47.74	**	2.00		73.41	**
	willingness to use matching services	5.18		0.99		56.79	**
	willingness to use services managing food close to expiry dates	−43.25	**	−1.44		−10.91	
	tolerance of using commercial meal kits	−39.10	**	−2.62		−17.84	**
	tolerance of using commercially prepared dishes	22.95	**	2.31		0.11	**
	willingness to use ingredient deliveries	6.61		2.21		6.26	
	willingness to use shopping-helper service	46.42	**	3.12	*	8.57	
	willingness to support the stores that take efforts to reduce food loss	24.96	**	−1.95		6.41	
Social x Perceptional dimension							
	willingness to use AI cooking devices	−51.37	**	0.23		−5.80	
	willingness to use inventory management APP	−72.83	**	−11.75	**	−134.11	**
	willingness to use matching services	12.53		10.87	**	−20.31	
Highly urbanized region ×	willingness to use services managing food close to expiry dates	32.38		2.38		6.24	
	tolerance of using commercial meal kits	−1.78		−0.87		31.55	
	tolerance of using commercially prepared dishes	−29.27		−11.17	**	−27.85	
	willingness to use ingredient deliveries	67.53	**	−5.29		49.75	*
	willingness to use shopping-helper service	33.95	*	8.24	*	15.94	
	willingness to support the stores that take efforts to reduce food loss	−40.54	**	−5.64		−35.70	
Behavioral dimension							
	cooking effort	−0.34	**	1.99	**	−0.26	**
	inventory check for food loss reduction	−53.99	**	−7.69	**	−13.15	
	food preservation innovations to reduce food loss	−27.84	**	−7.27	**	−30.96	**
	using mail order and home delivery of foodstuffs	33.45	**	0.95		22.17	**
	Number of observations	13,750		13,750		13,750	
	adj.R2	0.057		0.114		0.073	

*represents the 10% significance level, and **does the 5% significance level.

that are generating more food waste. If appropriate guidance is implemented to convert "perception" into "behavior", food waste can be reduced. Similarly to food-related household emissions, the features may change if considering the impact of both social and personal dimensions. The use of information and communication technology in regions undergoing a transition in a social environment can improve the sophistication of the management of smart food systems and eliminate waste in a variety of ways. According to our results, several perceptional changes (being more willing to use AI cooking devices, use inventory management APPs, and support the stores that make efforts to reduce food loss) may reduce food waste in highly urbanized regions. Turning perceptional drivers into behavior changes can be realized by transitioning to smart eating habits. Consequently, people's behavior based on environmental consciousness can bring a better outcome. The significant negative impacts can lead to the hypothesis that if the transition is driven by both perception and social environment, a desirable synergistic effect of reducing food loss can be achieved.

Behavioral changes may significantly reduce food waste. Households that frequently freeze their food in small portions to preserve and use later and check inventories before going shopping generate all types of food waste (food loss, plastic wrappings, kitchen waste). These reductions are not observed when changes stay in the perceptional stage (i.e., coefficient of willingness to use inventory management APP not significantly negative), again indicating the importance of converting "perception" into "behavior".

4. Discussion

When stocktaking the current business activities of the small and medium-sized enterprises providing smart food services in Japan, regardless of whether they receive subsidies from the government or target household customers, we found that one category of them has a large potential to accelerate such conversion from "perception" into "behavior" (MAFF, 2022). Their APPs (or online platforms) provide positive affirmation to any user behaviors that help reduce food loss. The affirmation, though essentially another form of offering discounts (e.g., get one free in the future after several purchases, lower prices offered by the food retailers), is in a very entertaining form (e.g., collecting stamps/points for kids, a game-style design with "tasks" and "rewards"). These gamified features not only incentivize household users to engage with smart food services regularly but also serve as subtle nudges towards adopting more sustainable food consumption habits, slowly shifting from perceptional changes to behavioral changes.

Smart food services have the potential to improve the quality of life for elderly families, single households, and those who have difficulties accessing local food outlets. However, those potential users may perceive various types of smart food services differently. Our results of Japan's case show that households are more willing to try services that offer immediate benefits (they can use them in "one step"), compared to the useful information that requires "two steps" to be fully utilized. Switching to a lifestyle with more utilization of smart food services also may not reduce household carbon footprints and food waste simultaneously. What we found in this work may also applied to countries, similar to Japan, with lower food self-sufficiency, high population density, and rather advanced social and technological infrastructure (such as South Korea, Singapore, etc.). This might be especially true for urban populations where space constraints and busy lifestyles make daily shopping challenging.

One inevitable limitation regarding the survey implementation is that the responses are all collected online, which leads to a sampling bias where the least digitalized household would be unlikely to take this survey. Also, our question design of asking 3-contínous-day dinners can effectively capture the behavior patterns of the cook, namely how the cook would manage the inventory and how often the cook would go shopping for ingredients. However, this would inevitably lead to the disability to capture the seasonal patterns of dinner menus, and our results mainly represent winter menus.

5. Conclusion

In this paper, we conducted a questionnaire survey to collect information from 5500 households in Japan from both highly urbanized and other regions. We proposed a multi-dimensional framework to include all drivers of smartization (shift to smarter eating habits and using more smart food services), including social drivers (measured by the social infrastructure in regions with different levels of urbanization), technological drivers (measured by the usage intensity of convenience food), perceptional drivers (measured by multiple self-reported indicators), and behavioral drivers (measure by the cooking effort, and multiple other self-reported indicators). With the detailed assessment of both direct and indirect household food-related emissions, the corresponding attitudes towards smart food services and smart eating habits collected from a large sample size survey, and the smart food transition framework with multiple dimensions, we investigated what may affect food-related household carbon footprints and wastes.

In the context of a better social infrastructure (e.g., better telecommunications infrastructure or higher penetration of SNS) where households can have a higher level of welfare and better access to smart food services, additional food waste would be generated but not necessarily food-related greenhouse gas emissions. We then conducted a further breakdown of their drivers, namely the contributions of perceptional changes and behavioral changes, to a possible reduction in such carbon footprints and wastes.

Our results show that households are more willing to try services that offer immediate benefits (they can use them in "one step"), compared to the useful information that requires "two steps" to be fully utilized.

Regarding the carbon footprints, perceptional changes such as being more willing to use services managing food close to expiry dates can also be good drivers to reduce food-related household emissions. Behavioral changes, on the other hand, may significantly reduce household emissions. Households that frequently freeze their food in small portions to preserve and use later, check inventories before going shopping, and put in more cooking effort, generate less overall carbon footprints. This is achieved not through reducing the heating time (reducing the emissions from cooking) but through cutting the unnecessary consumption of food products and services (reducing the emissions embodied in the food supply chain).

Regarding food-related waste, behavioral changes may significantly reduce food waste. Perceptional changes such as being more willing to use services managing food close to expiry dates and more willing to use meal kits can be good drivers to reduce food waste. However, households that reported a higher level of willingness to use inventory management APPs, to use shopping-helper services, and to support the stores that make efforts to reduce food loss are the ones that are generating more food waste.

The additional food-related greenhouse gas emissions and wastes along with the smamization transition can be possibly improved by perceptional changes and behavioral changes. Our paper emphasized the importance of appropriate guidance for such perceptional changes and behavioral changes, together with detailed directions. In the future study, we plan to examine the synergistic effect of reducing household carbon footprints and wastes simultaneously.

CRediT authorship contribution statement

Sayaka Ita: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Ayu Washizu:** Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation, Funding acquisition, Conceptualization. **Yiyi Ju:** Writing – review & editing, Visualization, Validation, Software, Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

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