Food Disgust Sensitivity and Household Food Waste

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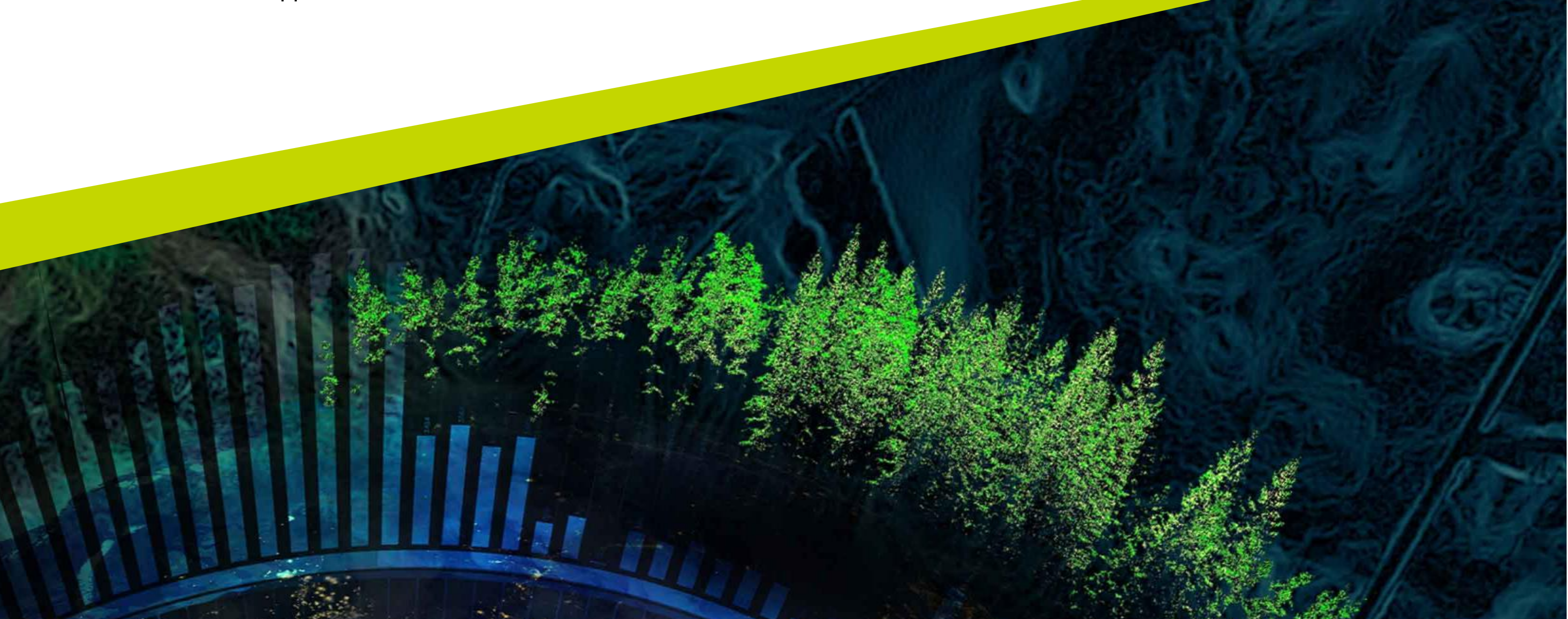

Food Disgust Sensitivity and Household Food Waste

Anna Maria Burian

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Abstract

Household food waste is shaped not only by practical factors but also by psychological processes that are not yet well understood. This study examined whether food disgust sensitivity — the tendency to experience strong disgust in response to food-related cues — is associated with objectively measured household food waste. Food Disgust Scale (FDS) survey data were collected from 36 households in Uppsala, Sweden, and linked to food waste measurements obtained through automated smart bin technology over monitoring periods averaging 749 days. Spearman's rank correlation was used as the primary statistical method. The primary hypothesis — that higher food-disgust sensitivity would predict greater food waste — was not supported. The association between FDS scores and per capita food waste was weak and negative ($\rho = -0.08$, $p = .641$), contrary to the direction expected based on prior self-report research. The study was severely underpowered (7% power), meaning the null result cannot be interpreted as evidence against an effect. Household size was the only significant predictor ($\rho = -0.34$, $p = .040$), with larger households generating less waste per person — consistent with a well-established economies-of-scale effect. The negative direction of the FDS–waste association is discussed in terms of pre-purchase avoidance: high-FDS individuals may avoid purchasing foods that trigger disgust reactions, thereby reducing the amount of food that could potentially be discarded in the household. This mechanism is invisible to smart bin measurement. The study demonstrates the importance of objective waste measurement and highlights the need for larger, more representative samples in future research on psychological predictors of food waste.

Keywords: food disgust sensitivity, household food waste, smart bin, food disgust scale, sustainable food systems

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1. Introduction

Each year, approximately one-fifth of all food available to consumers is wasted globally, amounting to an estimated 1.05 billion tonnes annually (UNEP, 2024). At the household level, food waste reflects everyday decisions about what to buy, cook, and discard. These decisions are shaped not only by practical factors such as household size, shopping habits, and food storage, but also by psychological processes that are not yet well understood (Schanes et al., 2018). One psychological factor that has received growing attention is food disgust sensitivity — the tendency to feel strong disgust in response to food-related cues. Disgust evolved as part of the Behavioural Immune System, a set of mechanisms that motivate avoidance of potentially contaminated or spoiled food (Schaller, 2006; Terrizzi et al., 2013). Individuals who are more easily disgusted by food may therefore be more likely to perceive still-edible food as unacceptable and discard it prematurely — a mechanism that could contribute to avoidable household food waste (Egolf et al., 2018). Consistent with this, Egolf et al. (2018) found that individuals with higher food disgust sensitivity reported discarding food more frequently.

However, a critical limitation of existing research is that food waste has almost exclusively been measured through self-report (Schanes et al., 2018; Egolf et al., 2018). Self-reported waste is known to underestimate actual disposal behaviour by approximately 30% on average, due to social desirability bias and recall errors (Van Herpen et al., 2019). The present study combines Food Disgust Scale (FDS) survey data with objective food waste measurements collected via automated smart-bin technology from 36 households in Uppsala, Sweden. Smart bins record the weight of each disposal event continuously and passively, providing a long-term objective measure of actual disposal behaviour that is independent of respondent recall or social desirability. To the author's knowledge, this is the first study to examine the association between food disgust sensitivity and objectively measured household food waste.

1.1 Aim

The primary aim of this study is to examine whether food-disgust sensitivity is associated with the amount of household food waste generated per capita. A secondary aim is to explore whether additional sociodemographic and behavioural variables are associated with food waste in this sample.

2. Background

2.1 Food Waste globally

Household food waste is a significant contributor to global resource loss: the production of food that ultimately goes to waste is responsible for an estimated 8–10% of global greenhouse gas emissions and occupies nearly 30% of the world's agricultural land (UNEP, 2024). For the purposes of this study, food waste is defined as food intended for human consumption that is instead discarded, lost, or left to spoil at the household level (UNEP, 2024). In response, the United Nations established Sustainable Development Target 12.3, which calls for halving per capita food waste at the retail and consumer levels by 2030 (UN, 2017), connecting food waste reduction to broader goals including climate action (SDG 13) and ending hunger (SDG 2). Food waste levels vary considerably across regions, shaped by factors such as climate, infrastructure, and cultural practices — for example, higher outdoor temperatures are associated with faster spoilage, and rural households in middle-income countries tend to waste less as food scraps are more commonly redirected to animal feed or composting (UNEP, 2024).

Although international frameworks such as the UNEP Food Waste Index and the EU measurement methodology have established common definitions, significant variation remains in how food waste is measured across studies. Baquero et al. (2023) reviewed 109 European food waste ratios and found values ranging from as low as 3 to as high as 450 kg per person per year — driven not by genuine behavioural differences alone, but by how food waste is defined, which supply chain stages are included, and which measurement methods are applied. A particularly important definitional distinction concerns what counts as food waste in the first place (Baquero et al., 2023).

2.2 Avoidable vs. Unavoidable Food Waste

Not all food that enters the organic waste bin is equally problematic from a sustainability perspective. A key distinction is between avoidable and unavoidable food waste. Unavoidable food waste refers to parts not intended for human consumption under normal circumstances: bones, fruit stones, eggshells, and similar inedible fractions (WRAP, 2009). Avoidable food waste refers to food that was edible at some point prior to disposal — bread that went stale, vegetables not used in time, leftovers never reheated (WRAP, 2009; Nicholes et al., 2019). A third, potentially avoidable category includes food that some people would eat and others would not — potato skins or slightly overripe fruit (Nicholes et al., 2019). Crucially, Nicholes et al. (2019) also found that perceived edibility does not equal actual consumption — people frequently classified a food as edible in principle while reporting they would not eat it themselves, a gap that reflects the influence of individual preference, disgust, and habit. This distinction matters because avoidable and unavoidable waste arise from different causes, have different environmental impacts, and require different solutions (WRAP, 2009). It is avoidable waste — food that could have been consumed but was not — that is most closely linked to the psychological processes examined in the present study. If disgust sensitivity influences food waste, it is most likely through its effect on avoidable waste: a person who perceives a still-edible food as contaminated will discard it prematurely (Nicholes et al., 2019).

In practice, however, drawing this line is not straightforward. What counts as edible depends on cultural norms, individual preferences, and context — what is considered inedible in one country may be routinely eaten in another (Nicholes et al., 2019). The UNEP Food Waste Index includes both edible and inedible parts in its definition of food waste (UNEP, 2024). For research on psychological drivers of food disposal, this matters: when inedible fractions are included in the outcome variable, it becomes harder to detect a true link with behaviour. Beyond the question of what counts as food waste, accurately measuring how much is generated presents its own set of challenges, discussed in the following section.

2.3 Measuring Household Food Waste

2.3.1 Challenges in Measuring

Accurately quantifying household food waste is considerably more difficult than it might appear. Although common definitions have been established at the international level, challenges remain in how these definitions are operationalized across studies — including where to draw the boundary between edible and inedible food, and between avoidable and unavoidable discarding (Baquero et al., 2023; Corrado et al., 2019). A fundamental problem is that most people are poor judges of their own food waste. Self-report measures are subject to social desirability bias — people underreport behaviour they perceive as irresponsible — and recall bias, as food is discarded in small increments throughout the week (Van Herpen et al., 2019). Van Herpen et al. (2019) found that self-report methods underestimate food waste by approximately 30% on average compared to direct weighing. To address these limitations, researchers have turned to objective approaches such as waste composition analysis and direct weighing. These methods produce more accurate data but are labor-intensive, typically conducted over short periods of one to two weeks, and depend on participant engagement (Baquero et al., 2023; Withanage et al., 2021). Food disposal also fluctuates in response to holidays, travel, and seasonal variation — meaning short measurement windows introduce substantial uncertainty when extrapolating to annual estimates (Sjölund et al., 2025). These limitations motivate the use of automated, long-term measurement approaches, described in the following section.

2.3.2 Smart Bin Technology

An emerging approach is the use of automated weighing technology, also called smart bins or automated quantification tools (AQT). These devices consist of a digital scale placed under the organic waste bin, connected to a computer that records the weight of each disposal event along with a timestamp, without requiring any active input from the household. A camera positioned above the bin takes a photograph at each disposal event, providing an image record that can be used to verify unusual weight readings or to classify the type of food discarded — as implemented in Jones-Garcia et al. (2022) and Sjölund et al. (2025), whose infrastructure is also used in the present study. Because the system operates passively, it does not require households to remember to record their waste and can collect data continuously over weeks, months, or years — enabling the kind of long-term perspective that short-window studies cannot provide. Sjölund et al. (2025) applied this methodology in a Swedish household setting, monitoring 28 households over an extended period using the same automated quantification tool as in the present study, demonstrating that long-term passive measurement captures substantial variation in food waste both between and within households over time. A subsequent study by Sjölund et al. (2026) used the same infrastructure across 41 households, providing further evidence for the reliability of this approach. While the quantification methodology described above captures how much food is wasted, understanding why households discard food requires examining psychological determinants — among which disgust has emerged as particularly relevant (Schanes et al., 2018).

2.4 Disgust

Understanding household food waste requires looking beyond practical factors such as household size or shopping habits. Food-related decisions are also shaped by emotions and individual attitudes — and one emotion that has received growing attention is disgust (Schanes et al., 2018), who identified disgust and guilt as among the most frequently cited emotional responses associated with food discarding across 60 household food waste studies, establishing disgust as an empirically relevant driver of disposal behaviour. Disgust was first described as a basic human emotion by Darwin (1872), who noted its distinctive facial expression and its close connection to the rejection of offensive tastes and smells. In psychology, disgust refers to a feeling of revulsion at the prospect of contact with — and especially swallowing — something offensive or contaminating (Rozin & Fallon, 1987). It evolved from a simple distaste response into a broader pathogen-avoidance system, expanding to cover visual cues of decay, mould, bodily products, and contamination (Chapman & Anderson, 2012). What specifically triggers disgust is shaped by culture — almost all objects of disgust are of animal origin, but chicken feet, fish heads, and certain organ meats may be completely normal in one culture and deeply repulsive in another (Rozin & Fallon, 1987).

A distinction relevant to the present study is between distaste and disgust. Distaste is sensory-based: something tastes bad or smells off (Chapman & Anderson, 2012). Disgust is triggered by thoughts and associations — by what a food is or where it comes from, not just how it feels in the mouth (Chapman & Anderson, 2012). This distinction becomes important when evaluating the Food Disgust Scale (FDS). Individual differences in how strongly people experience food-related disgust — referred to as food disgust sensitivity — reflect stable, trait-like variation in how easily the disgust response is triggered by food-related cues (Hartmann & Siegrist, 2018). Food disgust sensitivity is domain-specific: being easily disgusted by certain foods does not mean a person is easily disgusted in other areas of life, such as moral violations (Tybur et al., 2009). It is also distinct from food neophobia — the tendency to avoid unfamiliar foods. Both predict food rejection, but food disgust sensitivity scores predict rejection even after controlling for neophobia, confirming they capture different psychological processes (Ammann et al., 2018; Egolf et al., 2018). Research consistently finds that women score higher on food disgust sensitivity than men, and age is also associated with FDS scores, though direction varies across studies (Al-Shawaf et al., 2017; Egolf et al., 2019; Ozturk & Ozgen, 2023). These demographic patterns informed the choice of control variables in the present study. To understand why food-disgust sensitivity varies among individuals and how it might shape behaviour, it is necessary to consider the broader psychological system in which disgust operates.

2.5 The Behavioural Immune System and Food Waste

Disgust functions as part of a larger psychological system known as the Behavioural Immune System (BIS) — a set of mechanisms that evolved to motivate pathogen avoidance before contact occurs (Schaller, 2006). Rather than fighting infection after the fact, the BIS scans the environment for cues of contamination and responds with disgust and avoidance. The chain works like this: a sensory cue triggers the BIS, which activates disgust, prompting the person to avoid or reject the stimulus. This happens quickly and often without much conscious deliberation (Terrizzi et al., 2013). Terrizzi et al. (2013) describe the BIS as a stable personality-level trait: some individuals have a more sensitive, easily triggered BIS than others, and these differences are measurable, which is exactly what the FDS captures. The BIS is not a perfectly calibrated system. It was designed for an environment in which eating something dangerous could be fatal, making false alarms evolutionarily cheap compared with the cost of a miss (Terrizzi et al., 2013). In a modern food environment, however, this tendency can lead to the rejection of perfectly safe food (Rozin & Fallon, 1987). A banana with brown spots, milk that smells slightly different, or food stored in a container that previously held something disgusting may all trigger a disgust response — even when no real danger exists. Rozin and Fallon (1987) demonstrated this in an experiment where people refused soup stirred with a brand-new flyswatter. The object had never touched anything dirty – but the mere idea of the association was enough to make the food feel unacceptable. This false-alarm pathway describes a direct theoretical link between food disgust sensitivity and avoidable household food waste: individuals with a more sensitive BIS may discard still-edible food simply because something about it triggers their disgust response. This mechanism forms the basis of the present study's primary hypothesis.

2.6 The Food Disgust Scale

For years, food disgust sensitivity has been discussed in the literature without a reliable instrument to measure it specifically. The general disgust scales that existed — most notably the Disgust Scale developed by Haidt, McCauley, and Rozin (1994) — covered many domains at once: animals, bodily products, sexual disgust, moral violations, and food. While useful for broad disgust research, these scales were not suited to studying food-related behaviour specifically, as they mixed food-relevant and food-irrelevant items into a single score (Hartmann & Siegrist, 2018). To fill this gap, Hartmann and Siegrist (2018) developed the FDS through a systematic five-study programme, identifying eight distinct categories of food-related disgust: animal flesh, poor hygiene, human contamination, mould, decaying fruit, fish, decaying vegetables, and living contaminants such as insects. The result was a 32-item comprehensive version and an 8-item short version (FDS-short) with one representative item per subscale, rated on a six-point Likert scale from 1 (not disgusting at all) to 6 (extremely disgusting). The FDS-short demonstrated good reliability and convergent validity through correlations with general disgust sensitivity, food neophobia, and picky eating (Hartmann & Siegrist, 2018). Critically, Ammann et al. (2018) validated the scale using actual behavioural tasks: FDS scores were significantly and negatively correlated with consumption of meat, banana juice, and insect chocolate — and associations held after controlling for food neophobia — demonstrating that the FDS predicts what people actually do, not just what they say. The FDS-short was subsequently validated across ten countries in a sample of 6,128 participants, with metric invariance confirmed across Western countries (Egolf et al., 2019). The Swedish subsample provided a direct reference point for the present study. The FDS is specifically designed to capture pathogen-based food disgust and explicitly excludes moral disgust, as the two are psychologically distinct processes (Tybur et al., 2009).

2.7 Food Disgust Sensitivity and Food Behaviour

Research consistently shows that higher FDS scores predict reduced consumption of disgust-eliciting foods (Ammann et al., 2018). The strongest associations are for animal-derived products, consistent with the expectation that pathogen-based disgust is functionally specialized toward foods of animal origin (Tybur et al., 2016). Higher FDS scores are also associated with more selective everyday eating and picky eating in adults (Kauer et al., 2015; Ozturk & Ozgen, 2023), and with higher perceived risk of food contamination hazards (Siegrist et al., 2020). Together, these findings establish food disgust sensitivity as a stable, behaviourally relevant trait that shapes how people evaluate, select, and consume food. The most directly relevant prior study is Egolf et al. (2018), who found that FDS scores were significantly and positively associated with self-reported food waste frequency in a large Swiss sample, an association that remained significant after controlling for food neophobia. However, both the predictor and the outcome were self-reported, meaning the association may partly reflect shared method variance rather than a genuine behavioural relationship. Whether food disgust sensitivity is associated with objectively measured household food waste remains unknown — a gap the present study addresses by combining FDS survey data with smart bin measurements from 36 households in Uppsala, Sweden.

3. Materials & Methods

3.1 Research Design

This study investigates the relationship between food-related disgust sensitivity and household food waste generation using a quantitative, cross-sectional research design (Döring & Bortz, 2016; Kuß et al., 2014). Smart-bin food waste data was linked with self-reported survey responses at the household level. The research comprised three steps: (1) questionnaire development and data collection, (2) collection and processing of smart-bin food waste data, and (3) statistical analysis integrating both data sources. The following hypotheses were tested:

H1: Higher food disgust sensitivity is positively associated with the amount of household food waste generated per capita.

H0: There is no significant association between food disgust sensitivity and household food waste per capita.

3.2 Study Sample

3.2.1 Recruitment and Response Rate

The study sample consisted of 44 households in Uppsala, Sweden, equipped with smart bins as part of ongoing food waste research conducted by the Department of Energy and Technology at SLU. Smart bin data for these households had already been collected prior to this thesis; the present study made use of this existing dataset by linking it to newly collected survey data on food disgust sensitivity. As the households were recruited from this existing infrastructure, they constitute a convenience sample — a non-probability sampling approach in which participants are selected based on availability rather than random selection (Kuß et al., 2014; Raab-Steiner & Benesch, 2015). All 44 households were invited to participate in the survey; of these, 36 provided complete responses and are included in the analysis, corresponding to an approximately 82% response rate.

Of the eight non-responding households, seven showed their last smart-bin registration in mid-to-late 2025, suggesting they had left the project prior to the survey period (February–April 2026). One household (HH37) remained active until April 2026, indicating continued engagement despite not completing the survey. Non-response among the remaining seven households may therefore primarily reflect project dropout rather than survey fatigue.

In addition to the primary Uppsala sample, 12 households from a parallel smart bin monitoring project in Gothenburg, Sweden were included in a supplementary analysis. These households used identical smart bin infrastructure and the same active-day normalisation approach, making the data directly comparable. No survey data were collected from Gothenburg households; this supplementary dataset was used solely to test the robustness of the household size finding from the primary analysis.

3.2.2 Sample Characteristics

The majority of respondents identified as female (n = 23), with a mean age of 43.7 years. Two-person households were most common (n = 16), and just under half reported no children (n = 16). Most respondents were in full-time employment (n = 29), and educational attainment was high, with 80% holding a master's or doctoral degree (n = 29). Dietary patterns were diverse, with omnivorous and flexitarian respondents comprising the largest groups. Full sample characteristics are provided in Table 1.

Table 1: Sample Characteristics (n=36)

Characteristic	n	%
Gender		
Female	23	64
Male	13	36
Age (years)	M = 43.7, SD = 14.9	
Household size		
1 person	9	25
2 persons	16	44
3 persons	2	6
4 persons	7	19
5 persons	2	6
Children in household		
No children	16	44
With children	11	30
Single households	9	25
Employment status		
Full-time	29	80
Part-time	1	3
Retired	5	14
Student	1	3
Education level		
Upper secondary	1	3
Vocational training	1	3
Bachelor's degree	5	14
Master's degree	17	47
PhD	12	33
Dietary pattern		
Omnivorous	18	50
Flexitarian	11	30
Vegetarian	5	14
Pescatarian	1	3
Vegan	1	3

3.3 Data Collection

Data were collected through two complementary sources — a self-administered online questionnaire and automated smart-bin weight measurements — which were subsequently linked at the household level using anonymized household codes.

3.3.1 Questionnaire

Food disgust sensitivity was assessed using the eight-item short version of the Food Disgust Scale (FDS-short), originally developed and validated by Hartmann and Siegrist (2018) across five studies. The scale exists in a 32-item full version and an 8-item short version. The short version was validated by Ammann et al. (2018), who showed that FDS scores predicted food-related behaviour beyond food neophobia. Internal reliability has been reported as adequate ($\alpha = 0.78$; Hartmann & Siegrist, 2018). In consultation with one of the scale's authors, the 8-item short version was selected for the present study to reduce participant burden while maintaining reliable measurement. Items are rated on a six-point Likert scale ranging from 1 (not disgusting at all) to 6 (extremely disgusting). The use of an even-numbered response format prevents respondents from defaulting to a neutral midpoint (Raab-Steiner & Benesch, 2015). The questionnaire was available in both English and Swedish (Appendix).

Self-report measures are susceptible to social desirability bias, where respondents may answer in socially acceptable ways rather than accurately (Raab-Steiner & Benesch, 2015). This is particularly relevant for food waste, which may be perceived as undesirable behaviour (Olatunji & Cisler, 2009). The present study addresses this by combining self-reported FDS scores with objectively measured smart-bin data. In addition to the FDS items, several complementary questions were included to capture household characteristics, dietary habits, leftover management, and food-related decision-making. Some items were adapted from related research projects within the department to ensure comparability across studies. The final questionnaire (Appendix) consisted of 31 items structured into four sections: (1) sociodemographic characteristics, (2) dietary habits and food avoidance, (3) cooking and leftover behaviour, and (4) food-related attitudes and disgust sensitivity (FDS items). Most questions used categorical response formats or Likert-type scales.

The questionnaire underwent a two-stage pretest as recommended by Raab-Steiner and Benesch (2015): a qualitative pretest with three participants (using feedback and cognitive probing techniques) and a quantitative pretest with eight participants (assessing survey flow, completion time, and data usability). No major structural issues were identified, and the questionnaire was finalized after minor adjustments.

The survey was then administered online using Netigate from 24 February to 04 April 2026. Reminder emails were sent on 9 March, 12 March, and 24 March; remaining non-respondents were contacted individually via email, using contact details already on file from the ongoing smart bin monitoring project. Data were immediately pseudonymized by replacing identifying information with household codes (e.g., HH01, HH02). Each household was asked to ensure that the person mainly responsible for food purchasing, cooking, and food management completed the questionnaire. The survey could only be completed once per link, and each participant responded at a single point in time, consistent with a cross-sectional survey design (Döring & Bortz, 2016).

3.3.2 Smart Bin Data

The smart bin infrastructure used in this study was already in place through ongoing research at the Department of Energy and Technology at SLU and was adopted as-is rather than designed specifically for this thesis. The long monitoring periods and passively collected objective waste data would have been unattainable within the scope of a single master's thesis; however, certain design choices were fixed in advance and could not be modified. The implications of these constraints are discussed in Section 5.10.

Food waste was recorded using smart bins — digital scales that automatically weigh each disposal event and store it with a timestamp, without requiring any active input from the household. It is important to note that the smart bins capture only one waste stream: food deposited in the designated organic waste bin. Food discarded via other routes — including the kitchen drain, the residual waste bin, or composting — was not recorded and is not reflected in the outcome variable. No distinction was made between avoidable and unavoidable waste, as image-based categorisation was not feasible given the volume of data and the scope of this thesis. Total recorded weight from the organic waste bin was therefore used as the outcome variable.

To enable comparison across households, food waste was normalised per capita using active-day normalisation following Sjölund et al. (2025, 2026):

kg/person/day = (total kg waste) ÷ (active days) ÷ (household size)

Active days are defined as days on which at least one weighing event was recorded. This approach excludes days with no recorded waste events — which may reflect genuine zero-waste days, but equally may reflect holidays, vacation absences, or technical interruptions — and therefore better reflects actual household disposal behaviour on days when the household was present and generating waste.

3.3.3 Data quality

Prior to analysis, events with missing weight recordings (n = 2,326) were excluded, as these represent triggered measurement events with no recorded weight change. No negative weight values were present in the dataset, indicating that bin-emptying events had been processed prior to data export. The minimum recorded weight per event was 0.001 kg, and the maximum was 5.07 kg. The primary outcome was household food waste, expressed as kilograms per person per day. Total food waste per household was aggregated by summing all positive weight recordings (weight_diff > 0) over each household's full monitoring period. The primary predictor, food disgust sensitivity, was operationalized as the mean score of FDS items on a 1–6 scale. Internal consistency was assessed using Cronbach's alpha. A reduced 7-item version was computed after one item (FISH4: "The texture of certain fish in the mouth") showed low inter-item consistency with the overall scale ($\alpha = 0.45$); removing it improved reliability to an acceptable level ($\alpha = 0.60$). All primary analyses were therefore conducted using the 7-item version; the 8-item version is retained for comparison. Control variables included household size, presence of children, age of the primary respondent, dietary pattern, cooking frequency, and selected food planning and evaluation behaviours. Participants were additionally asked whether they were the main person responsible for food purchasing, cooking, and storage in their household (yes / shared equally / another adult), used in a supplementary analysis to assess whether the FDS–waste association differed by respondent role.

3.4 Statistical Analyses

All statistical analyses were conducted in R (version 4.3.2; R Core Team, 2023). Questionnaire and smart-bin datasets were merged using household codes. All personal identifiers were removed after merging. Prior to correlation analysis, normality was assessed using the Shapiro–Wilk test. FDS scores (7-item: $W = 0.966$, $p = .320$; 8-item: $W = 0.974$, $p = .536$) and food waste per capita ($W = 0.983$, $p = .848$) did not significantly deviate from normality. Nevertheless, non-parametric methods were chosen as the primary approach given the ordinal nature of the FDS scale and the small sample size (n = 36), as recommended for ordinal-level data (Kuß et al., 2014). Spearman's rank correlation (ρ) was used as the primary measure of association between FDS scores and food waste per capita, as well as between control variables and food waste. For the primary FDS–waste correlation only, Kendall's τ and Pearson's r are additionally reported to confirm the robustness of findings. Due to tied values in the ordinal data, approximate p-values are reported for Spearman's ρ. Internal consistency of the FDS was evaluated using Cronbach's alpha for both the 8-item and 7-item versions. Dietary group differences in FDS scores and food waste were assessed using the Kruskal–

Wallis test, a non-parametric alternative to one-way ANOVA appropriate for data that cannot be assumed to follow a normal distribution (Döring & Bortz, 2016). For two-group comparisons, Wilcoxon rank-sum tests were additionally applied. Group differences in binary discard reasons were assessed using Fisher's exact test, appropriate for small cell frequencies. Seasonal differences in monthly food waste were assessed using a Kruskal–Wallis test. Months were grouped into four seasons: Spring (March–May), Summer (June–August), Autumn (September–November), and Winter (December–February). A post hoc power analysis was conducted using the pwr package in R to assess the statistical power of the primary correlation test (Döring & Bortz, 2016). Statistical significance was evaluated at α = .05 throughout. A 95% confidence interval is shown for the primary FDS–waste correlation in Figure 1.

4. Results

4.1 Food Disgust Sensitivity (FDS)

Mean food disgust sensitivity was M = 2.54 (SD = 0.61) for the 8-item version and M = 2.56 (SD = 0.69) for the 7-item version, indicating moderate and comparable levels across both versions. Individual scores ranged from 1.25 to 4.00 (8-item) and 1.29 to 4.14 (7-item), reflecting moderate variability across participants on the 1–6 scale. Table 2 summarises the descriptive statistics and internal consistency for both FDS versions; individual FDS scores for all households are provided in the Appendix.

Table 2: Descriptive Statistics of FDS Scores

FDS Version	Cronbach's α	M	SD	Min	Max
8-item (full scale)	0.45	2.54	0.61	1.25	4.00
7-item (FISH4 excluded)	0.60	2.56	0.69	1.29	4.14

Note. Higher values indicate greater food-disgust sensitivity (scale range: 1–6).

4.2 Hypothesis Testing

The primary hypothesis was not supported. FDS scores showed a weak negative association with food waste per capita across all three correlation methods and both FDS versions, with no correlation reaching statistical significance at α = .05.

Table 3: Correlations between FDS Scores and Total Waste per Capita

Variables	ρ (Spearman)	p	τ (Kendall)	p	r (Pearson)	p
FDS 7-item — Waste/person/day	−0.08	.641	−0.05	.660	−0.01	.976
FDS 8-item — Waste/person/day	−0.11	.525	−0.07	.546	−0.06	.739

Note. *n = 36. Active-day normalisation (kg/person/day). No correlation reached statistical significance (α = .05). Approximate p-values reported for Spearman's ρ and Kendall's τ due to tied values.*

Figure 1 shows the relationship between FDS scores (7-item) and food waste per capita. The trend line is nearly flat, with only a marginal negative slope (ρ = −.08), suggesting that households with higher food-disgust sensitivity tend to waste marginally less food. The wide confidence interval and considerable scatter around the trend line indicate substantial variability across households.

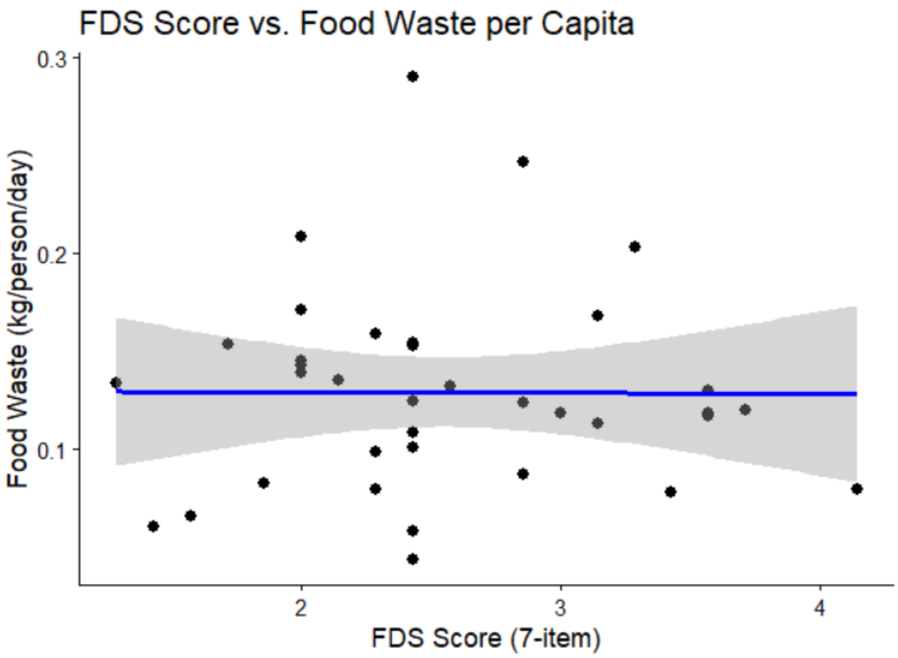

Figure 1: Scatterplot of FDS Scores and Food Waste per Person per Day across 36 Households

4.3 Respondent Role: Food Manager Analysis

Participants were asked whether they were the main person responsible for food purchasing, cooking, and storage in their household. Of the 36 respondents, 17 identified as the primary food manager, 18 reported shared responsibility, and one indicated that another adult was primarily responsible. When restricting the analysis to households where the respondent is the main food manager (n = 17), the negative association between FDS scores and food waste per capita was slightly stronger (ρ = −0.20 vs. ρ = −0.08 for the full sample), though still non-significant (p = .431).

4.4 Power Analysis

A post hoc power analysis was conducted using the pwr package in R to assess the statistical power of the primary correlation test. Power analysis estimates the probability of detecting a true effect given the observed effect size, sample size, and significance level. Results are summarised in Table 4. As the observed association was in the opposite direction to that hypothesized, one-tailed power is not reported for the primary FDS–waste test. Based on the observed correlation between FDS scores and food waste per capita ($\rho = -0.08$), and assuming $\alpha = .05$, the achieved statistical power with $n = 36$ was only 7% (two-tailed). This means that even if a true association of this magnitude exists in the population, the present study would have detected it in only approximately 1 in 14 replications. To achieve the conventional threshold of 80% power, a sample of approximately $n = 1{,}223$ households would have been required under a two-tailed assumption, or $n = 964$ under a one-tailed assumption.

For the food manager subsample ($n = 17$, $\rho = -0.20$), achieved power was 12% (two-tailed). To reach 80% power for an effect of this magnitude, approximately $n = 193$ food-managing respondents would be required under a two-tailed assumption, or $n = 152$ under a one-tailed assumption. The household size association ($\rho = -0.34$, $p = .040$) had 54% power (two-tailed); 80% power would require approximately $n = 65$ households. All power estimates are summarised in Table 4. The non-significant findings should therefore be interpreted with caution. The absence of statistical significance does not confirm the absence of an effect — it may reflect insufficient statistical power to detect a weak association.

Table 4: Post-hoc Power Analysis for Key Correlations

Scenario	n	ρ	Power (two-tailed)	n for 80% (two-tailed)
FDS × Waste (full sample)	36	−0.08	7%	1,223
FDS × Waste (food managers)	17	−0.20	12%	193
Household size × Waste	36	−0.34	54%	65

Note. Power calculated using the pwr package in R (α = .05).

4.5 Supplementary Analysis: Gothenburg Sample

The household size association (ρ = −0.34, p = .040) reached statistical significance but achieved only 54% power — meaning there remains a 46% chance of a false negative (failing to detect a true effect of this magnitude), not a false positive; the probability of a false positive is determined by the significance level (α = .05). To test whether this finding reflects a genuine effect rather than a sample-specific artifact, a supplementary analysis was conducted that included 12 additional households from a parallel smart bin monitoring project in Gothenburg, Sweden, yielding a combined sample of n = 48. All Gothenburg households used identical smart bin infrastructure and the same active-day normalisation approach, making the data directly comparable. This expansion was limited to household size as the sole variable of interest, as no FDS data were available for the Gothenburg households. Although the combined sample of n = 48 remains below the n = 65 required for 80% power, no additional comparable households were available at the time of analysis. Household size remained significantly associated with per capita food waste in the combined sample (ρ = −0.31, p = .035), consistent with the Uppsala-only result.

Table 5: Supplementary Analysis: Uppsala and Combined Sample Correlations

Variable	Uppsala n = 36	Combined n = 48
household_size × waste	ρ = −0.34, p = .040	ρ = −0.31, p **= .035**

Note. *Active-day normalisation (kg/person/day). The combined sample includes households in Uppsala (n = 36) and Gothenburg (n = 12) that use* *identical smart bin infrastructure. Bold values indicate statistical significance (p < .05). No FDS data available for Gothenburg households.*

4.6 Descriptive Statistics: Food Waste

4.6.1 Smart Bin Data

Smart bin data were available for all 36 households. Monitoring periods varied considerably, ranging from 190 to 1,797 days (M = 749.5, SD = 361.9), because households joined the smart bin project at different times. Coverage — the proportion of days within the monitoring period on which at least one weighing event was recorded — ranged from 26.6% to 92.6% across households (M = 69.8%), reflecting variation in how consistently households used the smart bin. After normalising for household size using active-day normalisation, per-capita waste ranged from 0.043 to 0.290 kg per person per day (M = 0.129, SD = 0.052, Median = 0.124). Expressed as an annual figure, this corresponds to approximately 47 kg per person per year – below the Swedish national household average of 60 kg per person per year reported by Naturvårdsverket (2024), though the national figure includes liquid food waste disposed of via the drain, which smart bins do not capture.

4.6.2 Monthly Trends and Seasonal Variation

Monthly average food waste per capita was examined for the period January 2024 to April 2026, restricted to months in which at least 50% of households contributed data ($n \geq 17$; range: 17–33 households), to ensure monthly averages were based on a sufficiently representative subset of the sample. Monthly averages ranged from 0.090 kg/person/day (January 2024) to 0.141 kg/person/day (August 2025). A general upward trend is visible throughout the observation period, as shown in Figure 2. Months were grouped into four seasons: Spring (March–May), Summer (June–August), Autumn (September–November), and Winter (December–February). Mean waste was highest in Autumn (M = 0.129, SD = 0.076) and Summer (M = 0.129, SD = 0.071), and lowest in Spring (M = 0.113, SD = 0.060) and Winter (M = 0.113). A Kruskal–Wallis test found no statistically significant seasonal differences ($H(3) = 4.79$, $p = .188$).

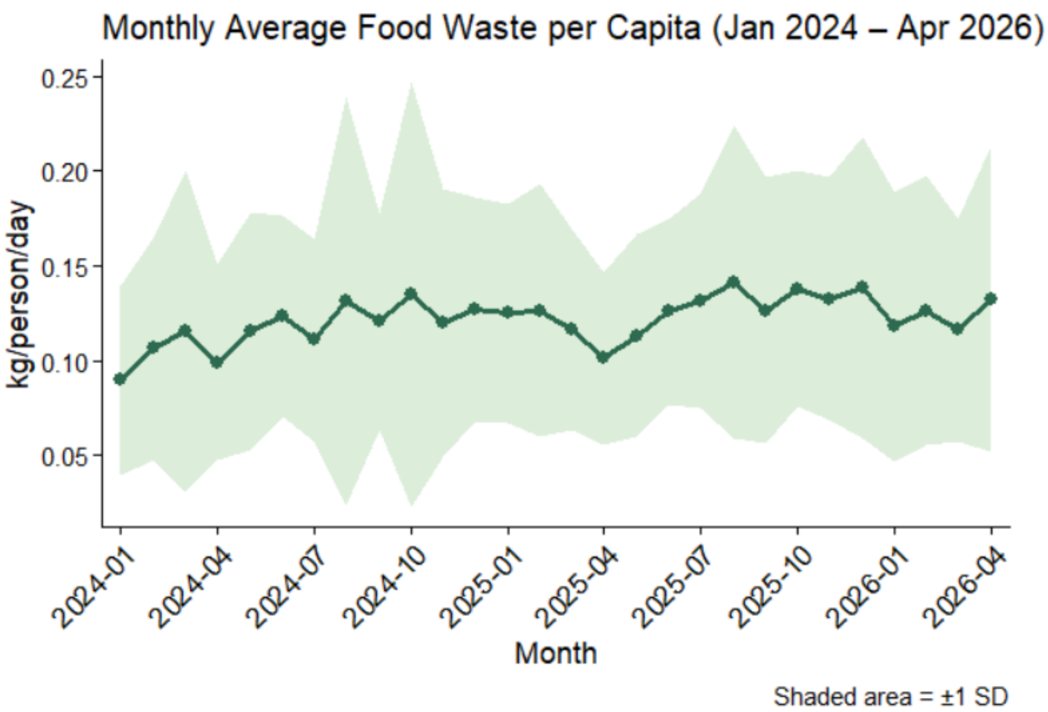

Figure 2: Monthly Trend Plot

4.7 Food Evaluation Scale and Food Waste

Spearman's rank correlation was calculated between per capita food waste and items from the Food Evaluation Scale, which assesses how households evaluate whether food is still safe or suitable to eat. Uncertainty about food safety showed a positive but non-significant association with per capita food waste ($\rho = +0.23$, $p = .172$). Avoiding food that is not at its best quality showed a similar non-significant positive association ($\rho = +0.24$, $p = .155$). Preferring to discard food even when the risk seems small ($\rho = +0.001$, $p = .996$) and willingness to eat food past its best-before date ($\rho = -0.20$, $p = .251$) were also not significant.

Table 6: Correlations between Food Evaluation Scale Items and Food Waste per Capita

Variable	**ρ**	***p***
Uncertainty about food safety	+0.23	.172
Avoiding food not at best quality	+0.24	.155
Discard even when risk seems small	+0.001	.996
Willing to eat past best-before date	−0.20	.251

Note. *n = 36. Approximate p-values due to tied values. α = .05.*

4.8 Control Variables and Food Waste

Spearman's rank correlation was calculated between per capita food waste and selected control variables to examine potential confounding factors. Household size showed a significant negative association with per capita food waste ($\rho = -0.34$, $p = .040$), indicating that larger households generated less per capita. All other control variables were non-significant.

Table 7: Spearman Correlations between Control Variables and Food Waste per Capita

Variable	**ρ**	***p***
Household size	−0.34*	.040
Age	−0.03	.866
Children	−0.27	.172
Meals at home	−0.01	.967
Leftover cooking frequency	−0.14	.408

Note. *n = 36. Approximate p-values due to tied values. * p < .05.*

4.9 Dietary Group Comparison

Due to the small and unequal group sizes across dietary categories (Omnivorous n = 18, Flexitarian n = 11, Vegetarian n = 5, Pescatarian n = 1, Vegan n = 1), dietary patterns were collapsed into two groups for statistical comparison: Omnivorous (n = 18) and Non-omnivorous (n = 18), the latter including flexitarian, vegetarian, pescetarian, and vegan respondents. Kruskal-Wallis tests revealed no significant differences between groups in FDS scores (7-item: $H(1) = 0.20$, $p = .655$; 8-item: $H(1) = 0.23$, $p = .633$) or food waste per capita ($H(1) = 1.94$, $p = .164$). Results were confirmed by Wilcoxon rank-sum tests (FDS 7-item: $W = 148$, $p = .667$; Waste: $W = 118$, $p = .171$).

Table 8: FDS Score and Food Waste by Dietary Group

Dietary Group	***n***	**FDS 7-item M (SD)**	**Waste kg/person/day M (SD)**
Omnivorous	18	2.60 (0.71)	0.135 (0.058)
Non-omnivorous	18	2.51 (0.68)	0.122 (0.046)

Note. *Non-omnivorous includes flexitarians (n = 11), vegetarians (n = 5), pescatarians (n = 1), and vegans (n = 1). No significant differences between groups were found for FDS scores or food waste (p > .05).*

4.10 Additional Analyses

Beyond the primary hypothesis, a set of exploratory analyses examined demographic and behavioural variables that are theoretically linked to food-disgust sensitivity or food waste. No significant association was found between FDS scores and either gender ($W = 180$, $p = .320$) or age ($\rho = -0.10$, $p = .572$). Among behavioural variables, considering whether food will be eaten before going bad showed a borderline positive association with food waste ($\rho = +0.30$, $p = .076$), and spontaneous purchasing a borderline negative association ($\rho = -0.28$, $p = .098$), though neither reached significance at $\alpha = .05$. Leftover cooking frequency was not significantly associated with food waste ($\rho = -0.14$, $p = .408$). When respondents were divided into high and low FDS groups based on the median FDS-7 score, the low FDS group showed a numerically higher tendency to discard food due to appearance, smell, or texture (42.9% vs. 18.2%), though this difference did not reach statistical significance ($OR = 3.25$, $p = .140$), and food waste per capita did not differ significantly between groups ($M = 0.130$ vs. 0.127 kg/person/day). All results are summarised in Table 9.

Table 9: Additional Analysis: FDS and Behavioural Variables in Relation to Food Waste

Analysis	**ρ / W**	***p***
FDS × Household size	$\rho = -0.22$	.191
FDS × Leftover frequency	$\rho = -0.14$	.427
FDS × Meals at home	$\rho = -0.11$	.542
FDS × Avoid meat	$W = 185.5$	.423
FDS × Avoid fish	$W = 135.5$	.619
FDS × Avoid dairy	$W = 40.5$	.676
FDS × Avoid eggs	$W = 34.0$	.121
Meal planning × Waste	$\rho = +0.30$†	.076
Spontaneous purchasing × Waste	$\rho = -0.28$†	.098
Mental energy × Waste	$\rho = -0.13$	.458
Portion estimation × Waste	$\rho = -0.01$	.960
Leftover frequency × Waste	$\rho = -0.14$	.408

Note. *$n = 36$. All associations were non-significant at $\alpha = .05$. † $p < .10$ (borderline).*

5. Discussion

Household food waste is shaped by a broad range of sociodemographic, behavioural, and psychological factors. Among sociodemographic variables, household size is one of the most consistent predictors across studies (Koivupuro et al., 2012; Schanes et al., 2018). Behavioural factors such as meal planning, shopping habits, and leftover management are also frequently identified as drivers of avoidable waste (Schmidt & Matthies, 2018; Schanes et al., 2018). At the psychological level, anticipated guilt, environmental awareness, and attitudes toward waste have been associated with food waste reduction behaviour (Etim et al., 2025; Schanes et al., 2018). The present study contributes to this literature by examining food disgust sensitivity — an emotional trait that has received comparatively little attention as a predictor of objectively measured waste.

5.1 Main Finding

The primary hypothesis — that higher food disgust sensitivity would be associated with more household food waste — was not supported: the association was weak, negative, and non-significant, contrary to the direction found by Egolf et al. (2018) in a large Swiss self-report sample. The null result should not be interpreted as evidence against an effect, given the study's limited statistical power. Additionally, the positive association found by Egolf et al. (2018) may partly reflect common method bias, as both the predictor and the outcome were self-reported — a limitation that the present study avoids through objective smart bin measurements. The scatterplot (Figure 1) further illustrates the absence of a discernible pattern: the wide confidence interval and considerable scatter around the nearly flat trend line confirm that variability across households was substantial and unrelated to FDS scores.

One important difference between the present study and Egolf et al. (2018) is how food waste was measured. Egolf et al. (2018) used self-reported frequency data, which are known to be affected by social desirability bias and recall errors (Van Herpen et al., 2019). As Giordano et al. (2019) demonstrated, questionnaires tend to capture intentions rather than actual behaviour — self-reported waste estimates systematically underestimate objectively measured disposal. The present study used objectively measured smart bin data, which capture actual disposal behaviour without relying on respondents' memory or willingness to report accurately. To the author's knowledge, this is the first study to test the FDS–waste relationship using objective rather than self-reported waste data. It is therefore possible that the positive association found by Egolf et al. (2018) was partly inflated by common method bias, in which both the predictor and the outcome were self-reported. This does not mean that FDS has no relationship with food waste, but it suggests that the association may be weaker or more complex than previously thought when actual behaviour is measured.

It is also worth noting that the smart bin data captured the total weight of organic waste, without distinguishing between avoidable and unavoidable components. Since FDS is theoretically most relevant to avoidable waste — food that is rejected because it is perceived as spoiled or contaminated — including inedible fractions in the outcome variable may have diluted any true association. This is particularly relevant given that, in a comparable Swedish smart bin sample, only 24.4% of total recorded food waste was classified as avoidable, with a further 7.3% possibly avoidable (Sjölund et al., 2026). The majority of what enters the organic waste bin — bones, peels, coffee grounds — is simply not subject to disgust-driven decision-making.

5.2 Pre-Purchase Avoidance

The negative direction of the observed association between food disgust sensitivity and food waste can be explained by the concept of pre-purchase avoidance, rooted in the Behavioural Immune System (BIS) framework (Schaller, 2006; Terrizzi et al., 2013). The BIS evolved to motivate pathogen avoidance before contact occurs — triggering disgust and cautious behaviour in advance rather than fighting infection after the fact. Individuals with higher FDS scores have a more sensitive BIS, meaning they react to potential contamination signals at a lower threshold, and tend to favor false alarms over misses (Terrizzi et al., 2013). Applied to everyday food behaviour, high-FDS individuals may avoid buying certain foods altogether — products close to their use-by date, slightly discolored meat, or anything with an unfamiliar texture or smell. If these foods never enter the household, there is nothing to throw away. Raudenbush (1995) documented this upstream avoidance through "won't-try" foods — foods categorically refused before any contact. However, disgust may also operate in the opposite direction once food is already in the household. Food that was initially acceptable can become disgusting over time — through spoilage, discoloration, or smell — triggering disposal even when the food might still be edible (Rozin & Fallon, 1987). Schanes et al. (2018) identified disgust as one of the most frequently cited emotional responses associated with food discarding across household studies, suggesting it operates as a disposal trigger rather than solely a purchase filter. Nicholes et al. (2019) further showed that people frequently classify food as still edible in principle while nonetheless discarding it — a gap that likely reflects disgust overriding rational judgment. In this case, higher FDS scores could lead to more waste, as individuals with a more sensitive disgust response may perceive food as unacceptable at an earlier stage of deterioration. These two mechanisms — pre-purchase avoidance reducing waste and in-household disgust increasing it — may therefore partially cancel each other out at the population level, producing a null association even in the presence of two real underlying effects. This interpretation is consistent with the near-zero correlation observed across all methods and both FDS versions.

5.3 FDS Scores and Sample Characteristics

Mean FDS scores in the present sample were noticeably lower than those reported in comparable studies: M = 3.52 in a Swedish subsample (Egolf et al., 2019) and M = 3.55 in a Turkish adult sample (Ozturk & Ozgen, 2023). The lower mean likely reflects self-selection: households voluntarily participating in a food waste monitoring project are probably more environmentally conscious and food-aware than average, resulting in systematically lower disgust scores and reduced variance, making associations harder to detect. Sjölund et al. (2025) noted the same pattern. The mean waste estimate of M = 0.129 kg/person/day is also lower than those reported by Sjölund et al. (2025; M = 0.159) and Sjölund et al. (2026; M = 0.140), and below the Swedish national household average of approximately 60 kg per person per year (Naturvårdsverket, 2024) – noting that the national figure includes liquid food waste disposed of via the drain, which smart bins do not capture. This likely reflects genuine sample differences — most importantly, the self-selected nature of the sample and the higher proportion of larger households — rather than a methodological artifact. Neither gender nor age showed a significant association with FDS scores, contrary to the well-documented pattern of women scoring higher than men (Al-Shawaf et al., 2017; Egolf et al., 2019). This most likely reflects insufficient power at n = 36. Koivupuro et al. (2012) found that single women generated the most food waste per capita — a pattern that could partly reflect higher disgust sensitivity in women, though this connection remains speculative without data on both variables within the same sample.

5.4 Scale Reliability and Item Removal

The full 8-item FDS showed low internal consistency in the present sample (Cronbach's $\alpha = 0.45$), below the commonly accepted threshold of $\alpha = 0.70$ (Döring & Bortz, 2016). Removing item FISH4 ("The texture of certain fish in the mouth") improved reliability to $\alpha = 0.60$, acceptable for short scales in applied research. All primary analyses were therefore conducted with the 7-item version.

The poor fit of FISH4 is not simply a statistical issue — it makes theoretical sense. Martins and Pliner (2006) showed that food disgust operates through two distinct dimensions: texture-based aversion and pathogen-based contamination disgust. These are statistically independent, and the FDS is designed to measure the latter. FISH4, which captures texture-based reactions, therefore does not align with the core construct. Tybur et al. (2016) add that fish occupies a culturally distinct category separate from other meat products — in a Swedish sample where fish is common and culturally normalised, texture-based reactions to fish are likely less pronounced. Supporting this, Egolf et al. (2019) found that the fish item showed one of the lower item-total correlations in their Swedish subsample ($r = .41$). Item removal based on insufficient item-total correlation is an established procedure in scale adaptation — Ayyıldız and Esin (2022) applied the same approach when adapting the Adult Picky Eating Questionnaire for Turkish adults. It should be noted that previous studies have retained FISH4, including the original validation by Hartmann and Siegrist (2018). The removal in the present study reflects a combination of the statistical threshold, the theoretical arguments above, and the cultural context of a Swedish sample — factors that, taken together, provide a justifiable basis for the adaptation.

5.5 Food Safety Uncertainty

Despite the lack of statistical significance, the direction of both associations is theoretically consistent with previous research indicating that uncertainty about date labels and food quality is one of the main reasons people throw food away (Schmidt & Matthies, 2018; Visschers et al., 2016). A key contributor to this uncertainty is the systematic confusion between "use by" and "best before" labels — where "use by" indicates a safety threshold while "best before" indicates quality, yet consumers frequently treat both as hard disposal deadlines (Corrado et al., 2019). When people cannot confidently judge whether a food is still safe, the easiest and most cautious response is to discard it — even when it would have been perfectly edible.

What makes this finding particularly interesting is its relation to the FDS framework. Siegrist et al. (2020) showed that food disgust sensitivity is associated with higher perceived risk of food-related contamination hazards — people with higher FDS scores tend to judge food as riskier. This suggests a possible indirect pathway: higher FDS scores could amplify food safety uncertainty, which in turn leads to more precautionary discarding. The present data cannot directly test this pathway, but it represents a hypothesis worth investigating in future research with larger samples and a design suited to mediation analysis.

5.6 Food Manager Subsample

When the analysis was restricted to the 17 households where the survey respondent was also identified as the primary food manager, the negative association between FDS scores and food waste was slightly stronger ($\rho = -0.20$) than in the full sample ($\rho = -0.08$), though it remained non-significant ($p = .431$). This pattern makes methodological sense: the FDS was completed by one person per household, but food waste is generated by everyone in the household. In the 18 households where food management was reported as a shared responsibility, the FDS score of one person may not accurately reflect the household's overall food-related decisions — the other adult, whose preferences, shopping habits, and disgust reactions also influence what gets bought and thrown away, was not surveyed. It is therefore not surprising that the association is slightly more detectable in households where the person who completed the survey is actually the one making most of the food-related decisions.

5.7 Household Size

Household size was the only variable to show a statistically significant association with per capita food waste ($\rho = -0.34$, $p = .040$), indicating that larger households generated less food waste per person per day. This is consistent with a well-established pattern across the food waste literature — Sjölund et al. (2025), Koivupuro et al. (2012), Schanes et al. (2018), and Di Talia et al. (2019) all report household size as one of the strongest and most consistent sociodemographic predictors of per capita waste, with single-person households generating the most. The most likely explanation is an economies-of-scale effect: larger households benefit from shared meal planning and more flexible portion use, while single-person households face a structural disadvantage as standard package sizes are designed for families, making it harder to consume all purchased food before spoilage (Koivupuro et al., 2012; Visschers et al., 2016). The replication in the combined Uppsala–Gothenburg sample ($n = 48$) confirms that the household size finding is not an artifact of the Uppsala sample specifically.

5.8 Null Findings

Most non-significant findings likely reflect limited statistical power rather than a genuine absence of effects. One notable gap is the absence of income data, which prevented examination of impulsive purchasing behaviour — a key driver of food waste (Di Talia et al., 2019). Gender showed no significant association with FDS scores, contrary to the well-documented pattern of women scoring higher than men (Al-Shawaf et al., 2017; Egolf et al., 2019) — most likely reflecting insufficient power. Given that Koivupuro et al. (2012) identified single women as the highest-per-capita waste group, the interplay among gender, disgust sensitivity, and food waste warrants investigation in larger samples. The lack of a significant difference between dietary groups is consistent with the small and unequal group sizes, which necessitated collapsing five dietary categories into two — a broad classification that likely obscured meaningful variation. For example, flexitarians and vegans were grouped together despite potentially very different food purchasing and disposal patterns. The descriptive trend was in the expected direction, with non-omnivorous households showing slightly lower FDS scores and less waste per capita, but the grouping approach was too crude to detect this reliably.

5.9 Statistical Power

With only 7% power, the null result does not prove that no effect exists — the study was simply not positioned to detect a weak association. This matters especially because the pre-purchase avoidance mechanism predicts a small negative effect by design, which is inherently harder to detect. Future studies should plan for adequate power from the start. By contrast, the household size association ($\rho = -0.34$, $p = .040$) was detected with the same sample size — suggesting the study was sensitive enough for medium-to-large effects, but simply too small to say anything reliable about weaker ones.

5.10 Limitations

A cross-sectional design was chosen as the most appropriate approach given the structure of the existing smart bin dataset, which provided long-term objective waste measurements but did not permit repeated survey administration. A longitudinal design would have enabled stronger causal inference but was beyond the scope of the present study. Several limitations of this design and the underlying data deserve explicit attention.

The most important limitation is the small sample size ($n = 36$). With only 7% power to detect the primary association, most null findings cannot be interpreted as evidence against an effect. The sample was also a convenience sample — households already participating in ongoing smart bin research at SLU. Volunteers in academic monitoring projects are likely more environmentally conscious and food-aware than the general population, which restricts the range of both FDS scores and waste levels and reduces the likelihood of detecting associations. This self-selection bias is further compounded by the unusually high educational attainment of the sample: 80% of respondents held a master's or doctoral degree, compared to approximately 19% of the Swedish population (Statistics Sweden, 2024). Highly educated individuals tend to be more food-literate and more motivated to reduce waste, further compressing variance in both the predictor and outcome variables. Taken together, the educational profile, self-selected recruitment, and volunteer nature of the sample mean that the present findings cannot be considered representative of Swedish households more broadly — the sample likely represents a narrow, atypically food-conscious segment of the population.

The smart bin infrastructure was adopted as-is from ongoing departmental research and was not designed specifically for the present study, meaning several measurement characteristics were fixed in advance. The smart bins capture only waste deposited in the organic waste bin — a single disposal route. Food discarded via the kitchen drain, placed in the residual waste bin, or redirected to composting is not recorded. Swedish Environmental Protection Agency data suggest that approximately 24% of household food waste is disposed of via the sewer rather than the organic waste bin (Naturvårdsverket, 2024; Sjölund et al., 2025), meaning a substantial fraction of actual food waste is systematically missed. Furthermore, some households may use multiple bins or disposal points within the home, of which only one was equipped with a smart bin scale, potentially capturing only a fraction of that household's total organic waste. It is also unknown whether households sorted their waste consistently throughout the monitoring period — a household that routinely disposed of organic waste in the residual bin would appear to generate less food waste, not because they wasted less, but because their organic waste was recorded elsewhere. This is undetectable in the data. Because sorting compliance is likely correlated with environmental attitudes, which may in turn correlate with both FDS scores and educational background, this represents a potential source of systematic rather than random error.

No distinction was made between avoidable and unavoidable waste. Sjölund et al. (2026) found that only around 24% of total smart bin waste in a comparable Swedish sample was avoidable, suggesting that the majority of organic bin contents are inedible fractions not subject to disgust-driven decision-making. Since FDS is theoretically most relevant to avoidable disposal, including inedible fractions in the outcome variable likely diluted any true association with disgust sensitivity. A Hawthorne effect cannot be excluded entirely — households aware of being monitored may have altered their disposal behaviour, and this effect is likely strongest among the most environmentally conscious participants. Finally, some households may fall below the 115 active-day threshold identified by Sjölund et al. (2025) as necessary for reliable per-capita estimates; three households had fewer than 200 active days (HH25: 89 days, HH24: 168 days, HH35: 148 days) and their estimates should be interpreted with particular caution.

The survey design introduces further limitations. The FDS was completed by only one person per household, while food waste is a shared outcome — a limitation discussed in detail in Section 5.6. The cross-sectional design precludes causal conclusions. Common method bias may partly explain the positive association found by Egolf et al. (2018), as both the predictor and the outcome were self-reported. Finally, questionnaire order effects cannot be ruled out, as the order of item presentation may influence disgust responses (Ammann et al., 2018).

5.11 Future Research

The findings of this study point to several areas where future work could build meaningfully on what was done here. The most immediate need is replication with a larger and more representative sample — based on the power analysis, at least n = 1,223 households would be needed to reliably detect a weak FDS–waste association. Future studies should also aim for greater socioeconomic and demographic diversity to avoid the self-selection bias present in smart bin project samples. A key methodological improvement would be separating avoidable from unavoidable waste. Since FDS is theoretically most relevant to avoidable disposal, using waste categorization methods — or emerging smart-bin image recognition technology — to distinguish edible from inedible fractions would better align the outcome variable with the construct being tested. Relatedly, measuring FDS for all food-managing adults in each household, rather than just one respondent, would substantially improve measurement validity and reduce the mismatch between the predictor and the outcome. Two theoretical pathways identified in this study also warrant direct empirical investigation. First, Siegrist et al. (2020) showed that FDS predicts perceived food contamination risk, suggesting that FDS may indirectly influence waste by amplifying uncertainty about food safety. A study with a larger sample and a mediation design could test this pathway directly. Second, research consistently shows that higher FDS scores predict greater picky eating and texture-based food rejection (Kauer et al., 2015; Egolf et al., 2018; Ozturk & Ozgen, 2023) — but whether more selective dietary habits lead to more or less household food waste remains untested. Future research, including a validated measure of picky eating alongside objective waste data, could help clarify this.

Finally, the consistently documented gender difference in food disgust sensitivity (Al-Shawaf et al., 2017; Egolf et al., 2019), combined with Koivupuro et al.'s (2012) finding that single women generate the most food waste per capita, points to a potentially important connection that has not yet been empirically tested. Future studies with sufficient power and gender-disaggregated data could explore whether disgust sensitivity partly explains this pattern. More broadly, future research should examine whether the association between FDS and food waste is moderated by household size and dietary pattern, and whether pre-purchase avoidance can be operationalized via purchase diary methods that complement smart bin measurement — a design that would allow the upstream effects of disgust sensitivity to be captured alongside actual disposal behaviour.

6. Conclusion

This study investigated the association between food-disgust sensitivity and objectively measured household food waste in 36 Swedish households using automated smart-bin technology. The primary hypothesis was not supported — FDS scores showed a weak, non-significant negative association with per capita food waste ($\rho = -0.08$, $p = .641$). The study was severely underpowered, and the null result should not be interpreted as evidence that no association exists.

The only significant finding was a negative association between household size and per capita food waste ($\rho = -0.34$, $p = .040$), consistent with a well-established economies-of-scale effect and replicated in a combined Uppsala–Gothenborg sample ($n = 48$). The negative direction of the FDS–waste association is theoretically interpretable through pre-purchase avoidance: individuals with higher disgust sensitivity may avoid purchasing risky or borderline foods, thereby reducing the amount of food that could be wasted in the household — a mechanism that smart bin data cannot capture.

Several limitations constrain the conclusions that can be drawn. The sample was small, self-selected, and likely more food-aware than the general population — reflected, for example, in the fact that 80% of respondents held a master's or doctoral degree — restricting variance in both FDS scores and waste levels. No distinction was made between avoidable and unavoidable waste, which likely diluted any true association with FDS. Future research should prioritize larger, more representative samples, distinguish between avoidable and unavoidable waste, and measure FDS for all household members. Testing the proposed pathway from FDS through food safety uncertainty to disposal behaviour via mediation analysis represents a particularly promising direction.

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Statement on the Use of Artificial Intelligence

Artificial intelligence tools (Claude, Anthropic; Grammarly, Grammarly Inc.) were used in the preparation of this thesis in the following ways: writing assistance, grammar and spelling correction, and general text formulation and editing. AI was also used to support R code development for statistical analyses and to assist with searching and reviewing the literature. No data were generated, fabricated, or analysed using AI tools. All research design, data collection, statistical analyses, interpretation of results, and conclusions are entirely the author's own work.

Popular science summary

Every year, households around the world throw away enormous amounts of food – food that took energy, water, and land to produce. To reduce this waste effectively, we need to understand why people throw food away in the first place. One factor that has received growing attention is disgust. Some people are much more easily disgusted by food than others — reacting strongly to the sight of mould, the smell of meat, or the texture of certain foods. This trait, known as food disgust sensitivity, could plausibly influence how much food people discard: someone who perceives day-old leftovers or a slightly overripe banana as unacceptable might be more likely to throw them away. This study tested that idea directly, combining survey data with objective food waste measurements from 36 households in Uppsala, Sweden. Food waste was recorded continuously using smart bins — digital scales that automatically weigh everything thrown away, without any effort from the household. Contrary to expectations, higher food-disgust sensitivity was not associated with greater food waste. The most plausible explanation is that people who are easily disgusted by food tend to avoid buying such foods in the first place — meaning less potentially problematic food ever enters the household. The smart bin only measures what gets thrown away inside the kitchen, not what was never purchased to begin with. The clearest finding was that household size mattered: larger households generated less food waste per person, consistent with a well-known economies-of-scale effect replicated across two Swedish cities. Until larger studies can test this more rigorously, the clearest message from this research is: if you want to reduce food waste in your household, the most effective lever is not your attitude toward disgusting food — it is the number of people sharing your dinner table.

Appendix

Food Waste Data per Household

Table 10: Food Waste Data per Household

Household	Household size	Active days	Waste (kg/person/week)	Waste (kg/person/day)
HH01	2	1116	0.422	0.060
HH02	5	970	0.302	0.043
HH03	4	1236	0.407	0.058
HH04	1	540	0.544	0.078
HH05	4	818	1.000	0.143
HH06	5	638	0.873	0.125
HH09	1	212	0.863	0.123
HH10	2	579	1.080	0.154
HH11	1	610	0.704	0.101
HH12	1	576	1.110	0.159
HH13	4	732	0.461	0.066
HH14	4	676	0.839	0.120
HH15	2	242	1.180	0.168
HH17	2	514	0.817	0.117
HH18	4	213	0.555	0.079
HH19	4	723	0.937	0.134
HH20	2	408	2.030	0.290
HH21	2	352	1.070	0.153
HH22	3	767	0.828	0.118
HH23	2	351	1.020	0.145
HH24	1	168	0.610	0.087
HH25	1	89	1.730	0.247
HH26	2	428	0.691	0.099
HH27	2	665	0.973	0.139
HH28	2	546	1.420	0.203
HH29	2	302	0.948	0.135

HH30	2	561	1.200	0.171
HH31	2	565	0.554	0.079
HH32	2	622	0.923	0.132
HH33	1	246	1.460	0.209
HH34	4	220	0.761	0.109
HH35	2	148	0.830	0.119
HH38	1	352	0.909	0.130
HH39	1	351	1.070	0.153
HH43	2	600	0.788	0.113
HH44	3	835	0.578	0.083

Note. *Active-day normalisation: waste divided by days with at least one recorded weighing event. Household size = number of persons. Waste values are rounded to three decimal places.*

Individual FDS Scores per Household

Table 11: Individual FDS Scores per Household

Household	FDS 8-item	FDS 7-item (FISH4 excluded)
HH01	2.00	1.43
HH02	2.25	2.43
HH03	2.75	2.43
HH04	3.12	3.43
HH05	1.88	2.00
HH06	2.62	2.43
HH09	3.00	2.86
HH10	2.25	2.43
HH11	2.38	2.43
HH12	2.25	2.29
HH13	1.75	1.57
HH14	3.38	3.71
HH15	2.88	3.14
HH17	3.38	3.57
HH18	2.75	2.29
HH19	1.25	1.29
HH20	2.25	2.43
HH21	1.88	1.71
HH22	3.75	3.57
HH23	1.88	2.00
HH24	2.62	2.86
HH25	3.00	2.86
HH26	2.12	2.29
HH27	1.88	2.00
HH28	3.00	3.29
HH29	2.50	2.14
HH30	1.88	2.00
HH31	4.00	4.14
HH32	2.62	2.57

HH33	2.25	2.00
HH34	2.25	2.43
HH35	2.75	3.00
HH38	3.25	3.57
HH39	2.75	2.43
HH43	2.88	3.14
HH44	1.88	1.86

Note. *FDS = Food Disgust Scale. Scores represent mean item ratings on a 1–6 scale; higher values indicate greater sensitivity to food disgust. The 7-item version excludes FISH4 (the texture of certain fish in the mouth). Values rounded to two decimal places.*

Monitoring Coverage % and Max Gap per Year

Table 12: Monitoring Coverage and Maximum Data Gaps per Household

Household	Total days	Coverage (%)	Maximum gap (days)
HH25	335	26.6	55
HH09	559	37.9	59
HH20	771	52.9	97
HH24	313	53.7	72
HH04	955	56.5	57
HH29	529	57.1	174
HH33	413	59.6	44
HH34	364	60.4	59
HH01	1797	62.1	94
HH43	960	62.5	46
HH17	814	63.1	28
HH15	381	63.5	35
HH21	552	63.8	71
HH14	1036	65.3	86
HH02	1484	65.4	71
HH12	878	65.6	28
HH11	895	68.2	16
HH38	480	73.3	71
HH06	868	73.5	144
HH22	1037	74.0	114
HH23	472	74.4	28
HH44	1105	75.6	62
HH10	760	76.2	41
HH28	710	76.9	118
HH32	809	76.9	42
HH39	453	77.5	42
HH35	190	77.9	9
HH05	1039	78.7	43
HH03	1547	79.9	108

HH26	526	81.4	28
HH13	894	81.9	40
HH31	678	83.3	47
HH30	639	87.8	11
HH18	234	91.0	14
HH27	723	92.0	16
HH19	781	92.6	13

Note. *Coverage = proportion of days within the monitoring period on which at least one weighing event was recorded. Maximum gap = longest single interval between consecutive weighing events. Households are sorted by coverage from lowest to highest.*

Questionnaire

This survey is part of a master's thesis at Swedish University of Agricultural Sciences (Department of Energy and Technology). Your responses will be linked to your household's food waste scale data via a unique technical survey link. No personal identifying information is collected in the questionnaire.
Participation is voluntary. You may withdraw at any time. The data are used for research only and will be handled confidentially. To include your household in the main analysis, please complete all questions; incomplete responses may have to be excluded.

Estimated time: 7 minutes.

1. Consent

Consent Check Box:

- ☐ I have read the information on the previous page and agree to participate in this study, including the use of the data for scientific research and publications.

Language

- ☐ English
- ☐ Swedish (svenska)
- ☐ American English

2. Demographics

What is your gender?

- ☐ Female
- ☐ Male
- ☐ Non-binary/third gender
- ☐ Prefer not to say

Are you the main person responsible for food management in your household (e.g., shopping, cooking, storing leftovers, etc...)

- ☐ Yes
- ☐ Another adult in the household
- ☐ Shared equally

What is your age?

____
____
____
____
____

How many people live in your household (including yourself)?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5
- ☐ 6
- ☐ 7
- ☐ 8
- ☐ 9
- ☐ 10
- ☐ >10

What is your current employment status?

- ☐ Full-time employment
- ☐ Part-time employment
- ☐ Self-employment
- ☐ Student
- ☐ Retired
- ☐ On long-term leave (e.g. parental leave)
- ☐ Unemployed
- ☐ Prefer not to say

What is the highest level of education you have completed?

- ☐ Compulsory school (primary/lower secondary)
- ☐ Upper secondary school (high school or vocational school)
- ☐ Vocational training/professional training after high school
- ☐ Bacherlor's degree
- ☐ Master's degree
- ☐ Doctoral degree (PhD)
- ☐ Prefer not to say
- ☐ Other (please specify): ______________________

3. Demographics

Are there children living in your household?

- ☐ Household without children
- ☐ Household with at least one child

4. Dietary Habits

Which of the following best describes your dietary pattern?

- ☐ Omnivorous (no general restriction)
- ☐ Vegetarian (no meat or fish)
- ☐ Pescetarian (no meat, but fish)
- ☐ Vegan (no animal products)
- ☐ Flexitarian (mostly vegetarian but occassionally meat/fish)
- ☐ Prefer not to say
- ☐ Others (please specify):

Which of the following food groups are deliberately avoided by you or anyone in your household? (Select all that apply)

- ☐ Meat
- ☐ Fish
- ☐ Seafood
- ☐ Dairy Products
- ☐ Eggs
- ☐ Nuts
- ☐ Soy
- ☐ Cereals
- ☐ None of the above
- ☐ Others (please specify): ________________________________

5. Intolerances

Are any of the foods you or somone in your household avoid eating due to allergy or intolerances?

- ☐ Yes
- ☐ No
- ☐ Prefer not to say

6. Cooking and Leftovers

On average, how many main meals (breakfast, lunch or dinner) are prepared at home in your household per week?

(Prepared at home includes cooking from scratch, reheating leftovers, or preparing simple meals such as sandwiches. It does not include ready-made meals that are only heated.)

3 meals x 7 days = 21 meals per week

- ☐ 0-5
- ☐ 6-10
- ☐ 11-15
- ☐ 16-21

When cooking, how often do you prepare more food than is eaten at the meal (i.e., leftovers are created)?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Always

7. Leftovers

When you prepare more food than is eaten at the meal, what are the main reasons for doing so? (Select all that apply)

- ☐ To have leftovers for later meals (e.g. lunch boxes)
- ☐ To save time on future cooking
- ☐ To make sure there is enough food at the meal
- ☐ Because it is difficult to cook smaller portions
- ☐ Because recipes or packages are sized that way
- ☐ Habit/I usually cook this amount
- ☐ Leftovers are rarely/never created
- ☐ Others (please specify): ______________________________

Typical reasons for discarding leftovers: (select all that apply)

- ☐ Forgotten/left too long
- ☐ Look/Smell/Texture concerns
- ☐ Unsure about safety
- ☐ No one wants to eat them
- ☐ Lack of time to use them
- ☐ Passed the best-before date
- ☐ Leftovers are rarely/never discarded
- ☐ Others (please specify): ______________________________

8. Planning & Coordination

Please indicate how much you agree or disagree with the following statements about your everyday food planning.

	Strongly disagree	Disagree	Slightly disagree	Slightly agree	Agree	Strongly agree
I often buy food spontaneously without having planned meals in advance.	☐	☐	☐	☐	☐	☐
When buying food, I consider whether it will be eaten before it goes bad.	☐	☐	☐	☐	☐	☐
I sometimes lack the mental energy to make careful decisions about planning and using food.	☐	☐	☐	☐	☐	☐

Please indicate how much you agree or disagree with the following statements about your everyday food planning.

	Strongly disagree	Disagree	Slightly disagree	Slightly agree	Agree	Strongly agree
In my household, household members differ in what foods they consider acceptable to eat.	☐	☐	☐	☐	☐	☐
In my household, it is difficult to coordinate meals and food use because household members have different schedules or plans.	☐	☐	☐	☐	☐	☐
I find it difficult to estimate how much food to prepare.	☐	☐	☐	☐	☐	☐

9. Food Evaluation

Please indicate how much you agree or disagree with the following statements.

	Strongly disagree	Disagree	Slightly disagree	Slightly agree	Agree	Strongly agree
When deciding whether food is still safe to eat, I often feel uncertain.	☐	☐	☐	☐	☐	☐
Even when the risk that food may not be safe seems small, I prefer to discard it rather than eat it.	☐	☐	☐	☐	☐	☐
I avoid eating food that is not at its best quality, even if it is still edible.	☐	☐	☐	☐	☐	☐
If food has passed its "best before" date but looks and smells fine, I usually eat it.	☐	☐	☐	☐	☐	☐

10. Food-Related Situations

Please indicate how disgusting you perceive the following products or situations to be.

	Not disgusting at all	Slightly disgusting	Moderately disgusting	Quite disgusting	Very disgusting	Extremely disgusting
To put animal cartilage (gristle) into my mouth.	☐	☐	☐	☐	☐	☐
To eat with dirty silverware in a restaurant.	☐	☐	☐	☐	☐	☐
Food donated from a neighbor whom I barely know.	☐	☐	☐	☐	☐	☐
To eat hard cheese from which mold was cut off.	☐	☐	☐	☐	☐	☐
To eat apple slices that turned brown when exposed to air.	☐	☐	☐	☐	☐	☐
The texture of certain fish in the mouth.	☐	☐	☐	☐	☐	☐
To eat brown-colored avocado pulp.	☐	☐	☐	☐	☐	☐
There is a little snail in the salad that I wanted to eat.	☐	☐	☐	☐	☐	☐

11. Follow-Up Interview

Would you be willing to participate in a short follow-up interview (approximately 20 minutes) about best-before labels and food use in your household?

- ☐ Yes, I am willing to be contacted for an interview
- ☐ No

12. E-Mail Address

Please provide your E-Mail address. Your contact information will be stored separately from your questionnaire responses to ensure data privacy.

___

___

___

___

___

Thank you for participating!

Your responses have been recorded. If you have any questions or are interested in the results, please conatact:

Email: anbu4909@stud.slu.se

Institution: SLU/Department of Energy and Technology

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