Current Research in Environmental Sustainability 9 (2025) 100292

Contents lists available at ScienceDirect

Current Research in Environmental Sustainability

journal homepage: www.sciencedirect.com/journal/current-research-in-environmental-sustainability

Unveiling the hidden patterns of household food waste

Amanda Sjölund [a,*], Christopher Malefors [a], Claudia von Brömssen [a], Erik Svensson [a], Pedro Brancoli [b], Samira Syed [b], Kamran Rousta [b], Mattias Eriksson [a]

[a] Department of Energy and Technology, Swedish University of Agricultural Sciences, Box 7032, SE-75007 Uppsala, Sweden
[b] Department of Resource Recovery and Building Technology, University of Borås, Högskolan i Borås, SE-50190 Borås, Sweden

ARTICLE INFO

Keywords:
Automated quantification tool
Household food waste
Waste measurement technology
Long-term monitoring

ABSTRACT

Among the methods commonly used for quantifying food waste in households, there are limitations that affect the reliability of quantification results. To address these, this study used an automated quantification tool to objectively and with high precision quantify food waste in 28 Swedish households for an extended period, reaching a total of 3945 quantification days. The results showed that the average daily waste amounted to 0.159 kg per person. Recorded food waste displayed a large variation between days, weeks and months, suggesting that long-term quantification is necessary for precision. As the results indicated, between 115 and 569 quantification days is necessary to provide an average estimate with a ± 10 % precision. This study presents empirical evidence demonstrating the feasibility and opportunities of automated food waste quantification, emphasizing the importance of extended measurement periods, high-frequency data collection, and minimal user intervention on designing effective waste tracking systems.

1. Introduction

Despite the widespread recognition of food waste hindering sustainable development, significant amounts of food continue to be wasted every year. In 2022, more than 1 billion tons of food were estimated to have been wasted at retail and consumption stages globally (UNEP, 2024). This estimate provides an indication of the effort required to reduce the vast amount of food waste generated, and make the food system more sustainable. To reduce food waste, different actions must be taken along the food supply chain. At the household level, finding strategies to reduce food waste is particularly important considering the amount of food waste generated there and the associated resource investments that are lost (Cattaneo et al., 2021; Casonato et al., 2023). An essential feature in this regard is to have an effective monitoring system in place that allows for baseline quantities to be established and for following up on any waste reducing action (Xue et al., 2017). Detailed monitoring of household food waste can also support more efficient reduction by providing information on specific consumer segments and what interventions should be targeting specific groups (Vittuari et al., 2023).

Current quantification methods used to obtain primary data on household food waste levels and composition includes more subjective approaches, such as questionnaire surveys, and food waste diaries where households self-report on their food waste quantities, along with more objective ones such as composition analyses of collected waste fractions carried out by local authorities (Elimelech et al., 2018). The methods used for monitoring food waste in households do, however, carry certain shortcomings, such as the limited timeframe under which quantifications are performed, the reliability of generated estimates, or the potential lack of understanding underlying causes behind the food waste (Withanage et al., 2021). Also, since timeframes are usually limited to one or a couple of weeks, yearly estimates that are based on data from those weeks become questionable considering that there are also weeks where food waste amounts may differ significantly, for instance during holidays when people are not at home. Consequentially, the estimated levels of food waste and the evaluated efficiency of interventions, becomes uncertain (Stöckli et al., 2018; Reynolds et al., 2019; Clement et al., 2023).

To address these shortcomings, efforts should be made to facilitate quantifications that objectively, and with high precision, track food waste levels in individual households long-term (Reynolds et al., 2019). Several examples of this can be found in the neighboring food service

* Corresponding author.
E-mail addresses: amanda.sjolund@slu.se (A. Sjölund), christopher.malefors@slu.se (C. Malefors), claudia.von.bromssen@slu.se (C. von Brömssen), erik.g.svensson@slu.se (E. Svensson), pedro.brancoli@hb.se (P. Brancoli), samira.syed@hb.se (S. Syed), kamran.rousta@hb.se (K. Rousta), mattias.eriksson@slu.se (M. Eriksson).

https://doi.org/10.1016/j.crsust.2025.100292
Received 13 January 2025; Received in revised form 28 March 2025; Accepted 15 April 2025
Available online 19 April 2025

sector where tools that incorporate a more technical approach for assessing food waste quantities have been developed (Leverenz et al., 2021; KITRO, 2024; Leanpath, 2024). However, there have also been attempts to deploy similar technology in a household setting, including visual analysis tools (Van Herpen and Van Der Lans, 2019; Roe et al., 2020; Cropley et al., 2022; Barker et al., 2023) and digital scales (Lim et al., 2021; Jones-Garcia et al., 2022). Findings from the food service sector have shown that applying technical solutions have the potential to alleviate the limitations of the more traditional quantification methods, such as allowing for longer quantification periods, facilitating more detailed evaluations of interventions, and providing more objective data where quantification practices do not rely on staff involvement (Malefors et al., 2024). These benefits could also be applicable in a household setting where, for instance, a reduced effort required by the households would enable long-term quantifications to be carried out to capture possible seasonal fluctuations (Adelodun et al., 2021) and the natural dynamic occurring within households (Aitken et al., 2024). Moreover, it has been shown that quantifications that rely on the active participation of the household risk losing a significant share of the participants along the way, especially if carried out for a longer period (Jansson-Boyd et al., 2024). This highlights the need for applying quantification methodology that minimizes the risk of drop-outs as quantifications should strive to be carried out over a longer timeframe to provide reliable estimates and to capture fluctuations over time.

Due to the lack of quantification methods that can facilitate long-term quantifications, only a few studies have continuously quantified food waste for over a month. Based on weekly food waste diaries, Bash AlMaliky and AlKhayat (2012) studied food waste in 20 Iraqi households for 8 months which appears to be the study with the longest continuous data collection so far. Nevertheless, the majority of household food waste estimates remains based on quantifications that have applied one of the traditional methods such as surveys, waste composition analyses, or food waste diaries to waste generated over one or two weeks (Withanage et al., 2021; Eičaitė and Baležentis, 2024). With such timely restrictions arises some questions. Firstly, how to handle quantification data that are based on one week when scaling up to yearly estimates. It is not uncommon for studies to quantify food waste for one or two weeks, present an average daily food waste estimate based on those days, and then multiply that estimate by 365 days to obtain a yearly estimate (see e.g. Silvennoinen et al., 2014; Szabó-Bódi et al., 2018; Ilakovac et al., 2020; Ioannou et al., 2022; Barker et al., 2023; Bilska et al., 2024; Eičaitė and Baležentis, 2024). It is questionable how accurate that yearly estimate would be as it is based on the assumption that all weeks of the year are the same or that the specific week of quantification is representative for all other weeks. Most likely there will be weeks when more food waste is generated (e.g. during holidays) and weeks when no food waste is generated (e.g. during summer vacation). How this affects the precision of estimates cannot be known unless food waste is monitored for longer periods. A second question is how long quantifications must be performed to establish reliable baselines with sufficient precision. These baselines are essential in intervention studies to accurately determine if an intervention has a reduction effect on food waste. Overall, by not addressing the time perspective of quantifications, aspects such as time-dependent fluctuations and precision are likely not captured, which leads to uncertainties in results.

To meet the calls for more reliable quantitative assessments of food waste in households, the primary aim of this study is to investigate food waste generated in households in a long-term perspective using an automated quantification tool (AQT). The obtained quantification data will be discussed and analyzed according to the long-term perspectives where it will be used to explore the required length of a quantification period to provide an estimate with a certain level of precision. Additionally, quantified food levels of individual households will be discussed in light of basic demographical aspects such as household size and composition.

2. Material and methods

2.1. Data collection

Food waste quantification was performed using an automated quantification tool (AQT), developed to automatically quantify food waste generated in households. The AQT is installed in households where the food waste is typically disposed of. It consists of a scale (model Kern PCB-6000-0 with a resolution of 1 g) connected to a Raspberry Pi single board computer (model 4, 2GB RAM) that records the weight of food items as they are thrown in the organic waste bin that is placed on the scale, along with the date and time of disposal. For verification of the quantified food waste, a Raspberry Pi camera (module 3), also connected to the computer, is placed above the bin, and every time the computer records a weight difference, the camera takes a photo. To ensure sufficient lightning for the camera, a LED-strip is set up above the bin. As the aim of this study was to assess the generated quantities of the food waste, not to determine its composition, the camera function was used only for cross-referencing to detect extreme events or suspected deviations of the quantitative data. Fig. 1 illustrates the AQT system.

Following installation in a household, the AQT continuously collects data as long as the scale is operating. The Raspberry Pi computer is connected to the household's Wi-Fi, allowing for all recorded data, including weight increases, pictures, and timestamps, to be systematically transmitted to the server for central storage and back-up. If Wi-Fi connection is lost, data are still recorded by the computer and then uploaded to the server once it regains internet connection. Data are recorded and collected per wasting occasion, and stored as rows in a database.

2.2. Participants and system boundaries

Participants were recruited based on a convenience sampling approach, consisting of both households personally known by the authors and households that were not known by the authors but were referred by those within the initial recruitment network. This snowball-like recruitment method expanded the sample beyond the authors' direct contacts. No strict inclusion or exclusion criteria were applied, but households were required to be willing to participate for an extended period and have the capacity to use the automated tool, e.g. by having a power outlet under the sink. The recruitment was a continuous process, leading to the AQT being installed in the households at different times, thus providing quantification periods of different lengths. To obtain information about the participating households, such as the number and

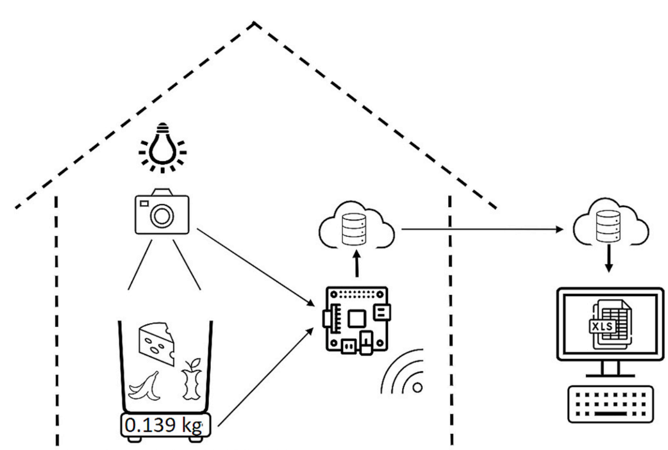

Fig. 1. Illustration of the automated quantification tool (AQT) system. Each time a new item is added to the bin, the weight and a photo of the item is recorded and uploaded to the database on the server from where it can be extracted.

age of residents, an online survey was sent to the participants after they had joined the study. In total, 28 households (70 people) participated, their demographic composition presented in Table 1. To ensure pseudonymity and confidentiality among the participants, their personal AQT was set up with a unique code that was further used when treating and analyzing data.

The overall system boundary of the study was set to all waste disposed of in the bin attached to the AQT, while no consideration was given to who was wasting the food (household member or guest), or to whether the wasted food was edible or not. Because the quantification methodology is restricted to capture only food waste that is disposed of in the bin attached to the AQT, this meant that primarily solid food was included and that also non-food items could be captured while, e.g., liquids poured down the drain, food waste given to pets, and wrongly sorted into another bin were not included.

2.3. Data filtering

While the AQT automates the data collection, some manual processing is required for analysis. Occasionally the AQT records weights without anything being wasted, which typically occurs when the bin has been removed and then placed back on the scale with a new empty bag. To remove such events from the data set, a few criteria were applied when extracting the quantification data from the server. The filter also took into consideration that the bin can be removed from the scale and replaced without being emptied, but with new waste added (e.g. when lifting the bin to the countertop to peel potatoes straight into the bin), and in such cases only included the added waste.

Recorded wasting events in the extracted data were ordered according to weight so that extreme events could be detected and further controlled. Verification of weights was made by cross-referencing each weight against the current, previous, and subsequent images corresponding to that weight. Data were removed if the item(s) displayed in an image was determined not to match the recorded weight (for instance when the recorded weight was 0.99 kg and the image showed only the peel of one orange). In the case of a bad or unclear image, data were assumed to be valid and therefore kept. In total, 272 recorded events had a weight registered above 0.350 kg, out of which 41 events (38.4 kg) were determined as measurement errors, giving an error rate of 15 % for the large events. The number of wasting events with a weight between 0.350 and 0.300 kg amounted to 105, out of which not one was determined a measurement error. A threshold for potential measurement errors was therefore set to 0.300 kg, giving that verification of weights was limited to wasting events with weights above 0.300 kg and that weights below that were all kept.

A similar filtering was then made for the number of wasting events between occasions where the food waste bag was replaced. This allowed to detect potential errors related to the equipment or software which were indicated by weights being registered multiple times but with no new item appearing in the images. The average number of wasting events between emptying occasions was 62 and if a period was detected to have registered more than 100 wasting events, those wasting events were crossed-referenced against their images. Data were removed if an error could be determined. If the images were unidentifiable, the recorded weights were kept in the data set. Finally, when the same weight had been registered more than twice at the same timestamp, those recordings were removed as this also indicated an equipment error. The filtering process gave a global error rate of 1.5 %. Fig. 2 shows a schematic overview of the data filtering process.

2.4. Data analysis

2.4.1. Statistical analysis

After passing the filter criteria, food waste quantities from each household were normalized to *kg food waste per person per day*. Hence, every day that a wasting occasion was registered, the sum of weight from all wasting occasions that day was divided by the number of people living in the household. Children below the age of one were excluded as their contribution to the overall food waste was considered insignificant or nonexistent. Derived daily observations of wasted food per person were then summarized into descriptive statistics per household.

Thus, an estimate of daily food waste per person could be derived from each household based on the total amount of wasted food, the number of household members, and the number of quantification days. Those individual estimates were then used to obtain an overall estimate of daily food waste per person, where the daily average estimates from each household were summed and divided by the total number of households:

$$\text{Total average daily food waste} = \frac{1}{h}\sum_{i=1}^{h}\left(\frac{1}{n}\sum_{j=1}^{n}\frac{\text{Recorded food waste}_{i,j}}{\text{People living in household}_i}\right) \tag{1}$$

where h is the number of households and n represents the number of quantification days for household i.

When inspecting the quantification data, it was found that people are not always at home or wasting items every day. Arguably, this creates implications when attempting to scale up a daily estimate that is based on days of food wastage to produce a yearly estimate. Therefore, to set this discrepancy in perspective, potential days when food waste could have been recorded, i.e. all days from the day when the AQT was installed to the last day of recording, were summed for each household and then used as the number of days which the food waste quantities were divided by. This provided a second daily estimate on waste per person that was based on the entire quantification period, accounting also for days with no food being wasted. In six of the households, the scale was known to have encountered some errors, leading it to not register any weights for a longer period (more than 3 weeks), despite food waste being generated. Those households were therefore excluded in this alternative analysis. In some of the remaining households, similar

Table 1
Demographic composition of participating households.

Demographic parameter	Households (n)
Household members	
1	6
2	10
3	5
4+	7
Age groups	
18–30	8
31–45	12
40–60	6
61+	2
Children in the household	
Yes	10
No	18
Age groups of children	
1–5	4
6–11	2
12–17	4

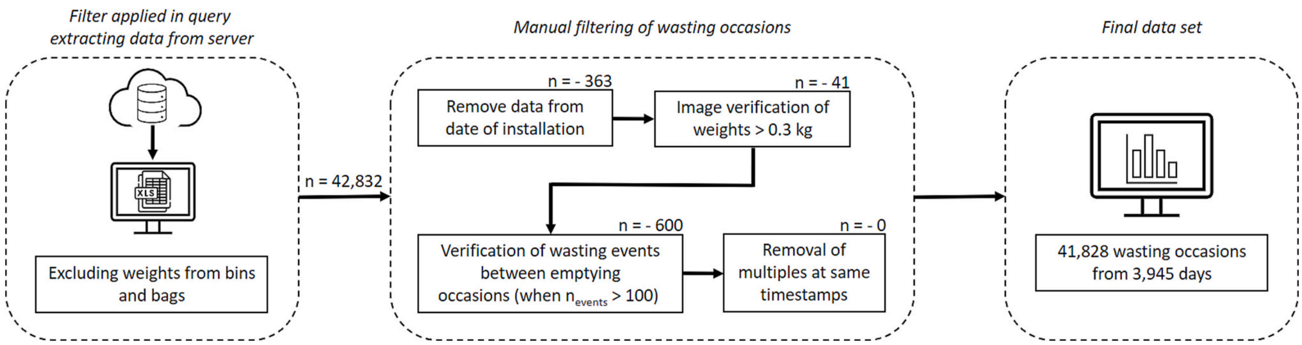

Fig. 2. Schematic overview of the data filtering process, n referring to the number of wasting occasions, which in the middle box indicates how many wasting occasions were removed at each step.

errors were also known of, but as they were more short-lived, they were not considered to significantly influence the results.

An important aspect in quantification schemes is to set the quantification period to be long enough to provide an estimate with a certain level of precision (Malefors et al., 2019). Since the number of days when people are not at home can vary between households, it is important to know how many days to base a quantification period on where food waste is actually recorded. According to the abovementioned distribution and characteristics of data, the number of required quantification days could be determined based on the confidence interval which uses the mean estimate of the sample and the standard deviation. Hence, to determine the required length of a quantification period based on a certain precision of the mean estimate, the average daily food waste per person for each household, from the days with recorded food waste was used accordingly:

$$n_{days} = \left(t_{1-\alpha/2}\frac{\sigma}{L}\right)^2 \tag{2}$$

where α is the desired level of confidence (0.05), σ is the standard deviation, and L is half of the desired length of the confidence interval, which was set to both ±5 and ± 10 % of the mean estimate. Although the distribution of observations of daily food waste per person was highly skewed for all households, the average could be approximated to a normal distribution according to the Central Limit Theorem as the sample (in this case number of days) was large enough (Quinn and Keough, 2010).

Additionally, in many studies it is interesting to determine the precision of estimates based on fewer observations, e.g. one or a few weeks. To establish this, the normal approximation of the mean might no longer hold and a moving block bootstrap was used instead (Kunsch, 1989). This allowed for including the inherent structure of food waste – where what is wasted on one day may influence what is wasted (or not) the following day. The block sizes used to simulate how the length of a measurement period affects the variability of mean estimates were set to 7, 14, and 28 days to reflect common food waste quantification practices. For each block size, 1000 resamples were drawn and the mean daily food waste per person was computed for each resample. The moving block bootstrap was illustrated for two households for which long series were available. It also included only days with recorded food waste, meaning that days when no food waste was recorded were not accounted for. Results were visualized using a density plot with 95 % confidence intervals to illustrate variability across the different measurement periods.

2.4.2. *Variation over time*

To understand how food waste levels fluctuate over time, hourly, daily, weekly, and monthly variations were analyzed. Throughout the course of the study, additional participants were recruited, leading to the number of participants continuously increasing. Therefore, the timely variations analyzed did not include the entire timespan as in the beginning it would have been more sensitive to the addition of new participants. Consequently, weekly, daily, and hourly variation analyses were based on quantification days between January and mid-May 2024 where it was considered that the addition of new participants would not influence the overall average to a greater degree while still providing the long-term perspective to variations. However, the same approach was considered unsuitable for analyzing the variation between months as this would have led to only four months being included in the analysis. To include additional months, the analysis of monthly variation used data from those households who had been using the AQT since October 2023 and who had not encountered any technical issues exceeding 3 weeks during that period. From this subset of households ($n = 9$), monthly average waste between October 2023 and April 2024 were derived from all households separately, as well as jointly similar to Eq. 1 where days were replaced with months.

For a variation in food waste between days, quantification data from all households that had recorded any food waste on a specific day were used to provide a total daily average for that day, similar to Eq. 1. Similarly, for variation between weeks, quantification data from all households who had recorded food waste for at least one day of a specific week were used to derive a total weekly average for that week. To calculate the average amount of food waste for each day of the week, the per person total amount of food waste from all households recorded on each day of the week was divided by the total number of quantification days for all households. To illustrate the precision of the estimates, they were provided a 95 % confidence interval according to the t-distribution. Finally, the hourly variation used the total sum of food waste from all households (not per person) for each hour.

2.4.3. *Demographical analysis*

To determine if there were differences in food waste levels between different groups of households, boxplots were used to visualize spread of data while linear regression models were used to verify possible differences between the groups. In the models, the average estimates of daily food waste per person, including only days when food waste had been recorded, were set to the dependent variable which was tested against the presence of children, number of household members, and ages of household members, respectively. Only people aged 18 years and older were included in the analysis of the differences in food waste levels depending on ages of household members as the purpose was to test different age groups of adults. If household members (aged 18 and above) belonged to different age groups, their average age was used to assign the household to one of the age groups. The same approach was used for assigning households with multiple children who belonged to different age groups. Only children aged 1 or older were accounted for.

All analyses were made in the statistical software R, version 4.3.0 (R Core Team, 2023). The ggplot2 package (version 3.4.4) was used for data visualization (Wickham, 2016).

3. Results

Overall, the results demonstrated that the amount of food wasted in the participating households greatly varied, both within and between households. From the total 3945 quantification days, the AQT had registered 1535 kg of food waste from all households together, corresponding to a total average of 0.159 kg per person per day. The daily food waste per person did, however, vary between the minimum 0.001 (0 if accounting also for non-wasting days) to the maximum 1.797 kg, although 75 % of the observations were found to be lower than 0.198 kg. However, the remaining 25 % of the daily observations accounted for 51 % of the total food waste recorded where the contribution from each household differed. In three of the households, over half of the days with recorded food waste were days contributing to the 51 % of the overall food waste, whereas in four other households, less than 10 % of the days were days with correspondingly high recorded levels.

3.1. Baseline and precision

Daily quantification data from the days of recorded food waste provided an input to determine the number of quantification days required for an average estimate with a certain precision to it within each household. It was found that the required number of quantification days to provide an average estimate with a precision of ±10 % varied between 115 and 569 days between the households, with a median of 245 days. To obtain an estimate with a precision of ±5 %, the days required for the ±10 % need to be multiplied by 4. A summary of the results from each household is presented in Table 2.

Table 2 shows that only six of the households (HH01, HH02, HH08, HH09, HH12, and HH13) reached the required number of days for their average estimate to have a desired precision of ±10 %. In comparison, when using shorter timeframes, the moving block bootstrap showed that with increased length of a measurement period, the variability in estimated mean decreases while precision increases (Fig. 3). However, the improvement is rather limited. The longest simulated measurement period of 28 days indicated the least variability, leading to a 95 % empirical confidence band from 0.087 to 0.155 for HH02 and from 0.136 to 0.341 for HH06. This could be compared to a margin of error of 0.034 for HH02 and 0.103 for HH06, or that the confidence interval of the estimated mean would be ±30 % for HH02 and ± 53 % for HH06.

Further, if accounting for days where no food waste was recorded by the AQT, the average food waste per person per day was found to be 0.129 kg, compared to 0.150 kg. Hence, if not accounting for the fact that people are not always at home or that food is not wasted every day, average estimates risk being up to 47 % too high or, if averaging all households, around 19 % too high. The overall as well as the individual differences are presented in Table 3.

3.2. Long-term perspective

By analyzing the time-series variation, it was found that the amount of food waste varied over hours, days, weeks, and months. Although the monthly food waste varied to a somewhat high degree within each household, their collective average did not vary to the same extent, as illustrated in Fig. 4.

As Fig. 5 shows, the relative time-dependent variation in food waste increased with the granularity of time, where the day-to-day variation showed the largest fluctuations. However, both the day-to-day and weekly variation showed higher relative fluctuations than the monthly variation displayed above, despite being depicted in different scales. Additionally, the average daily food waste during the period between January and May was 0.149 kg per person whereas the weekly average was 0.878 kg per person which, if divided by seven days, would be 0.125 kg per person per day. The reason for this difference is because the daily averages are based on food waste from all households having recorded some that day whereas the weekly averages are based on food waste from all households who had recorded food waste in at least one day of that week.

Table 2
Results from each household presented in descriptive statistics, sorted on number of household members and the quantification days needed for ±10 % of mean. Days marked in bold in the two right-most columns illustrate that the household has reached its required number of quantification days.

HH members*	Place	Days (n)	Food waste per person per day (kg)							Quant. days needed for ±	
			Min	Max	1st Quartile	Median	3rd Quartile	Mean	Std. Dev.	10 % of mean	5 % of mean
1 (0)	HH21	46	0.008	1.016	0.128	0.219	0.380	0.294	0.228	231	924
1 (0)	HH14	56	0.006	0.599	0.089	0.122	0.208	0.177	0.141	244	975
1 (0)	HH20	116	0.005	1.797	0.148	0.283	0.505	0.347	0.279	248	993
1 (0)	HH18	117	0.005	0.779	0.058	0.104	0.166	0.136	0.122	309	1237
1 (0)	HH30	52	0.021	1.650	0.106	0.225	0.398	0.301	0.290	357	1426
1 (0)	HH17	99	0.006	1.208	0.042	0.095	0.204	0.161	0.196	569	2277
2 (0)	HH27	65	0.003	0.286	0.046	0.102	0.163	0.106	0.064	140	560
2 (0)	HH09	201	0.002	0.583	0.081	0.126	0.191	0.145	0.099	**179**	716
2 (0)	HH11	113	0.023	0.678	0.077	0.105	0.154	0.138	0.107	231	924
2 (0)	HH06	240	0.003	0.961	0.082	0.188	0.331	0.230	0.184	246	983
2 (0)	HH05	166	0.002	0.782	0.070	0.161	0.323	0.210	0.179	279	1116
2 (0)	HH29	61	0.006	0.620	0.061	0.096	0.184	0.142	0.123	288	1153
2 (0)	HH23	48	0.007	0.516	0.048	0.093	0.198	0.135	0.124	324	1296
2 (0)	HH03	163	0.002	0.582	0.033	0.079	0.188	0.126	0.122	360	1441
2 (0)	HH24	53	0.006	0.507	0.027	0.080	0.136	0.100	0.097	361	1446
2 (0)	HH15	152	0.002	0.922	0.044	0.085	0.167	0.144	0.164	498	1993
3 (1)	HH13	183	0.008	0.487	0.082	0.119	0.166	0.130	0.075	**128**	511
3 (1)	HH08	241	0.019	0.921	0.118	0.183	0.274	0.211	0.133	**153**	611
3 (0)	HH12	241	0.005	0.669	0.079	0.126	0.213	0.163	0.125	**226**	904
3 (0)	HH04	233	0.002	0.494	0.039	0.079	0.122	0.094	0.080	278	1113
3 (0)	HH00	287	0.002	0.823	0.026	0.069	0.128	0.104	0.122	529	2115
4 (2)	HH26	73	0.027	0.287	0.065	0.115	0.164	0.122	0.068	119	477
4 (2)	HH01	261	0.018	0.473	0.082	0.132	0.183	0.146	0.083	**124**	497
4 (2)	HH25	87	0.003	0.214	0.038	0.069	0.109	0.077	0.048	149	597
4 (2)	HH22	92	0.010	0.772	0.109	0.176	0.268	0.209	0.141	175	699
4 (2)	HH02	260	0.001	0.520	0.059	0.104	0.161	0.126	0.097	**228**	911
4 (2)	HH19	133	0.001	0.347	0.020	0.037	0.060	0.053	0.052	370	1479
5 (3)	HH10	106	0.001	0.337	0.075	0.115	0.157	0.126	0.069	115	461
Total		**3945**	**0.001**	**1.797**	**0.123**	**0.140**	**0.201**	**0.159**	**0.068**		

* Of which children between 1 and 18 years of age in parenthesis.

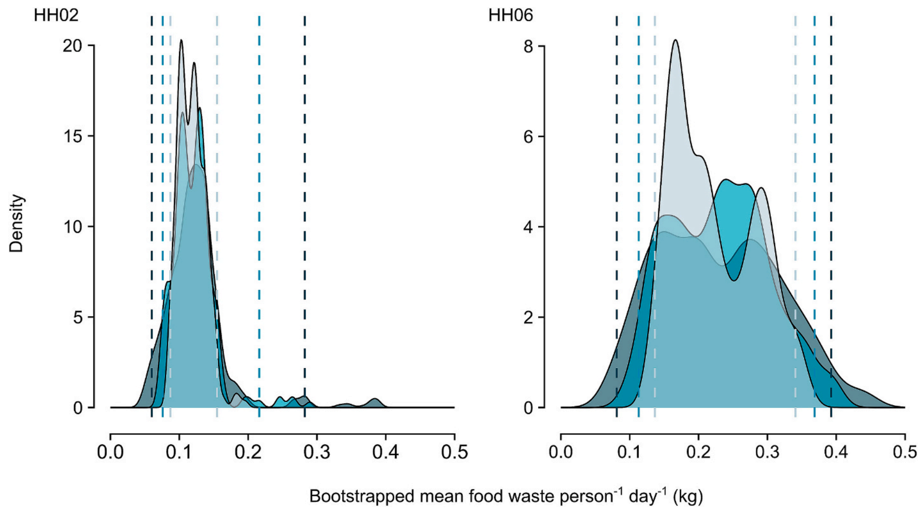

Fig. 3. Distribution of the daily mean food waste per person from the moving block bootstrap for household HH02 (left) and HH06 (right). Different colors representing the different measurement periods; 7 days (●), 14 days (●), and 28 days (●) with dashed lines illustrating the 95 % confidence bands.

Table 3
Difference in food waste estimations for each household depending on whether non-wasting days are accounted for. The overestimation column shows how much the average estimate would be overestimated if non-wasting days were not accounted for. Households with known scale malfunctions (longer than 3 weeks) are excluded.

Place	All days since start		Only days with registered food waste		Proportion of non-wasting days	Overestimation
	Days (n)	Mean FW/ person/ day (kg)	Days (n)	Mean FW/ person/ day (kg)		
HH18	172	0.093	117	0.136	0.32	47 %
HH23	69	0.094	48	0.135	0.30	44 %
HH00	403	0.074	287	0.104	0.29	40 %
HH15	212	0.103	152	0.144	0.28	39 %
HH20	153	0.263	116	0.347	0.24	32 %
HH13	235	0.101	183	0.130	0.22	28 %
HH03	208	0.099	163	0.126	0.22	28 %
HH02	329	0.099	260	0.126	0.21	27 %
HH01	329	0.116	261	0.146	0.21	26 %
HH19	154	0.045	133	0.053	0.14	16 %
HH04	268	0.082	233	0.094	0.13	15 %
HH06	274	0.201	240	0.230	0.12	14 %
HH09	229	0.128	201	0.145	0.12	14 %
HH26	81	0.110	73	0.122	0.10	11 %
HH29	68	0.127	61	0.142	0.10	11 %
HH08	258	0.197	241	0.211	0.07	7 %
HH10	111	0.121	106	0.127	0.05	5 %
HH11	118	0.132	113	0.138	0.04	4 %
HH25	89	0.075	87	0.077	0.02	2 %
HH12	242	0.163	241	0.163	0.00	0 %
HH27	65	0.106	65	0.106	0.00	0 %
HH30	52	0.301	52	0.301	0.00	0 %
Total	**4119**	**0.129**	**3433**	**0.150**	**0.14**	**19 %**

Finally, there was also a variation in recorded food waste quantities between days and hours of the day as illustrated in Fig. 6. Although more food waste in total was generated during weekdays, more food waste was recorded during weekends than regular weekdays when comparing each day in terms of food waste per person. Also, the time of day when waste was recorded was also more evenly spread out during weekends (Fig. 6).

The results also showed that food waste was being generated across almost all hours of day with a peak in the afternoon, both during weekdays and weekends, indicating behavioral and habitual differences

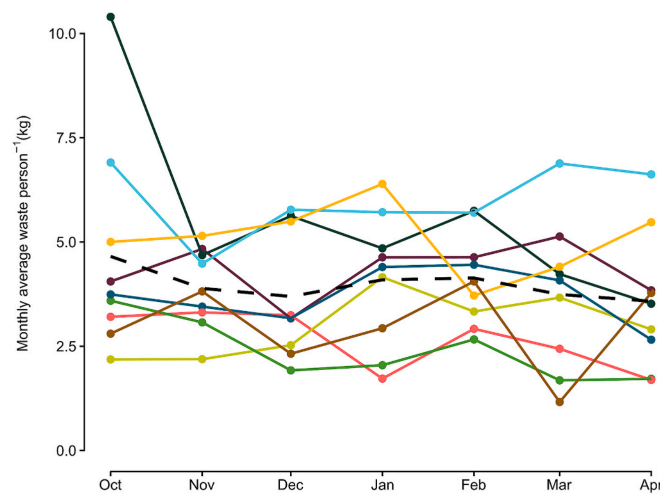

Fig. 4. Monthly variation of the 9 households who had quantified food waste since October 2023. Colors represent each individual household and dashed line in black illustrate their monthly overall averages.

between the households.

3.3. Insights to demographics

The demographical analysis showed that the more people living in the household, the lower the variation in daily waste per person, where the single-person households also showed to waste slightly more than the other households. Regarding the variation depending on ages of household members there was little difference found in median amount of food waste, although a slight discrepancy was found in the spread of daily observations where households with members of younger ages varied more. Also the presence of children did not influence the amount of food waste generated, although depending on the age of the children, a slight variation could be detected. The demographical influences on food waste amounts are shown in Fig. 7.

The linear regression model showed that single-person households wasted significantly more food than households with multiple members (p-values for households with 2, 3, and 4 or more members = 0.006, 0.019, and 0.002 respectively). There was no significant difference in average food waste levels between households with children and without ($p = 0.144$). Since the sample was too small to fit a linear

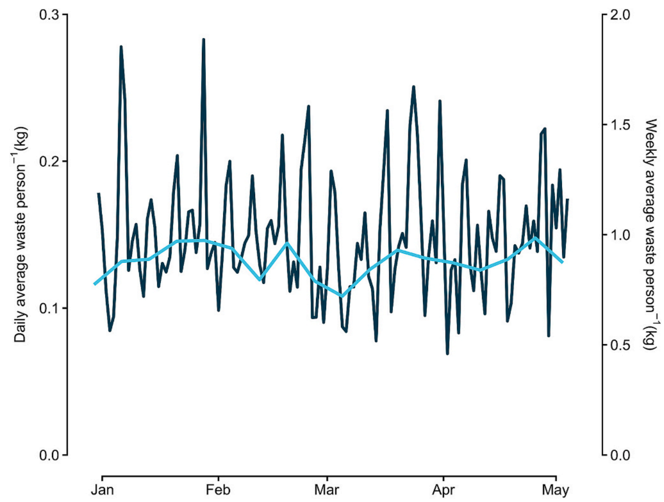

Fig. 5. Daily (●) and weekly (●) variations in recorded food waste between January and May 2024. Each daily average derives from the food waste of those households who had recorded something that day. Each weekly average derived from those households who had recorded something at least one day that week.

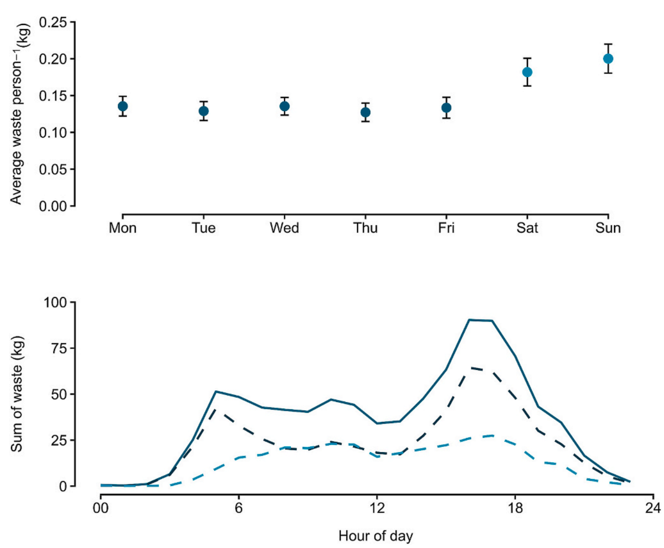

Fig. 6. Top graph illustrating variation in recorded food waste between weekdays (●) and weekends (●) with a 95 % confidence interval indicated by the error-bars. Bottom graph illustrating the sum of waste recorded at each hour of the day, in total (●), from weekdays (● dashed) and weekends (● dashed).

regression model to the households with children of different ages ($n = 10$), no test was made. Lastly, no significant difference in food waste levels was found between households with members of different ages.

4. Discussion

This study applied a long-term and objective approach for quantifying food waste in 28 Swedish households for a total of 3945 quantification days using an automated quantification tool. On average, the participating households wasted 0.159 kg of food per person per day, but the amount of food waste generated varied greatly over time, both within and between households. This variation in food waste generation was also discovered by Aitken et al. (2024) who concluded, in line with this study, that food waste needs to be monitored over time in which dynamic variations can be captured.

4.1. Insights from the long-term perspective

By utilizing the AQT, both objective and long-term collection of data could be facilitated as the households themselves did not have to engage in the quantification. A notable finding from the long-term perspective and the time-dependent variation in food waste levels was that if quantification is performed over e.g. one week, where food waste is generated and recorded each day, dynamics occurring within the household over longer time spans cannot be accounted for. Looking at some of the numerous studies that have investigated the amount of food waste generated within households, many can be seen to have taken a similar approach for presenting the obtained quantification data. Often based on one or two weeks of quantification, the daily average estimate gets aggregated to a yearly one by simply being multiplying by 365 days (see e.g. Szabó-Bódi et al., 2018; Giordano et al., 2019; Ilakovac et al., 2020; Bilska et al., 2024; Eičaitė and Baležentis, 2024). In such cases, researchers neglect the natural variation that occurs within the household over the course of a year, such as the fact that people are not always at home, and the variation between days when they are at home. As the findings of the present study suggest, the week or fortnight that is selected can have a significant effect on the results, where it is unlikely that it will be representative of the average week in a yearly perspective. Consequently, upscaling a daily estimate that is based on 7 or 14 days of quantification risks resulting in a misguiding yearly figure of the amount of waste generated, highlighting the importance of long-term perspectives.

The results of this study suggest that 14 % of the days, which approximates to one day per week, no food is wasted. This was also seen to vary greatly between households, ranging from food waste being generated all days to only 68 % of the days. Overall, if not accounting for non-wasting days, the results deriving from this study suggest that estimates that are based only on days when people are at home or wasting food could be about 19 % too high. Moreover, only 4 of the participating households had started their quantification before the summer holidays, which suggests that if including all households over a whole year, the overestimation could be even greater as indicated by those households (HH00,HH01,HH02,HH03). Accounting for non-wasting days is therefore arguably important when designing quantification schemes, which previous studies appear to have neglected. However, even though accounting for non-wasting days seems important, the main result of this study did not use this approach due to some uncertainties in the quantification methodology where the exact number of non-wasting days in all households was unknown due to equipment or system malfunction.

Another notable finding from this study is that the required length of a quantification period appears to be longer than what most studies are based on. The common food waste quantifications practices usually mean a week or two of measuring. However, as shown by the moving block bootstrap, such short quantification periods introduce variability to obtained estimates, making it difficult to draw reliable conclusions. This was true also for the longest simulated measurement period of 28 days, where the mean estimate of the moving block bootstrap had a confidence level of ±53 % for HH06 and ± 30 % for HH02. Two studies with the longest continuous quantification lasted for 166 days (Ramos et al., 2024) and 8 months (Bash AlMaliky and AlKhayat, 2012) respectively, although neither consisted of daily observations. Even within the present study, where a long-term approach was applied with a detailed level of quantification, only six of the households were found to have reached their required number of quantification days for the ±10 % precision. Meanwhile, none of the households were close to reaching the required number of days for the ±5 % precision which requires 4 times the amount of days compared to the ±10 %. However, in a practical perspective, the need for obtaining a ± 5 % precision may be unnecessary if considering its timely trade-off where quantification would need to be performed for several years in many cases. But a ± 10 % may be necessary to capture the effects of an intervention, which would require at least two times the suggested length to derive both a

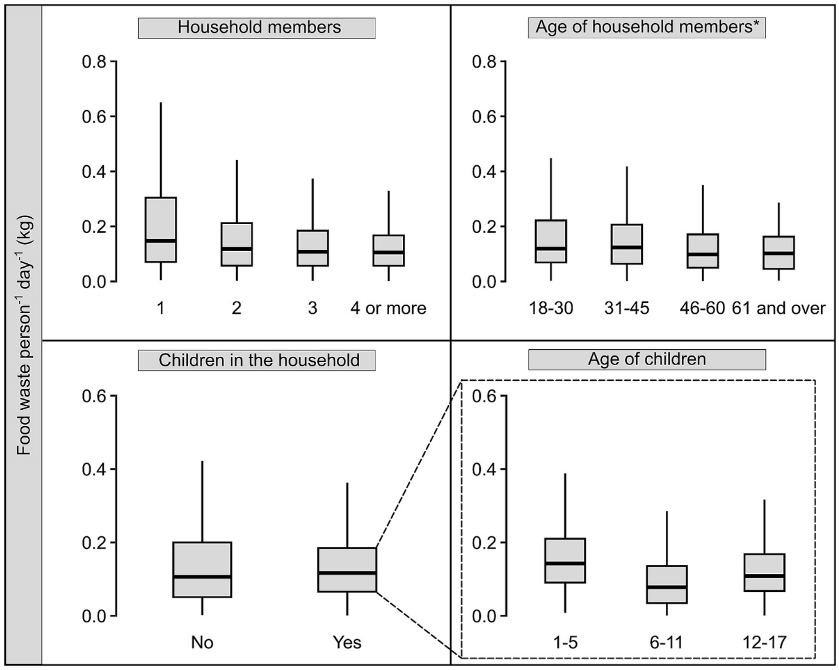

Fig. 7. Boxplots illustrating the distribution of quantification data based on certain demographical aspects. Boxes representing observations within the 25th and 75th percentiles, lines inside the boxes representing the median (50th percentile), and whiskers showing the smallest and largest values within 1.5*interquartile range (IQR). Outliers (observations beyond 1.5*IQR) are omitted. *18 years and older.

solid baseline estimate and a long-term evaluation of the intervention effects. It should also be borne in mind that the required number of quantification days was assessed at the household level and may differ when considered at a population level. To better understand the trade-offs between precision and effort at a population level, and to determine the optimal balance between the number of quantification days and the number of households, additional data and larger samples are needed beyond what was available in this study.

Concerning the time-dependent variation across days of the week and hours of the day, the results may have implications to intervention design. The variation in food waste generation between weekdays and hours of the day suggest that interventions should target weekends and weekday mornings and afternoons as these appear to be hot-spots for food waste generation. However, this relies on the assumption that the households are located in Sweden or a culture similar to Sweden where a majority of people do not eat their lunch at home but at work or school, at least during weekdays. As less people are home, less food waste is being generated. Moreover, this also assumes that food is wasted at the time it is generated, which might not always be the case. For instance, leftover food is sometimes stored with the intention of being consumed later but is instead discarded for various reasons. In such instances, the time of disposal does not accurately reflect when the food waste was initially generated, necessitating additional input from the households to provide a more precise timeline.

4.2. Demographics

It was found that the households with children did not waste more or less than the households without children (per person). This contradicts the results of Bilska et al. (2024) and Parizeau et al. (2015) who found that households with children wasted less than those without, but also Visschers et al. (2016) who found that households with children waste more. Thus, the presence of children seems to have different influences on the results in different studies, which could be a result of differences between the samples and/or uncertainties in the quantification. Also, households where the children were of the youngest age group (1 to 5 years) indicated to waste slightly more than the other two age groups which suggests that it might be useful to not only divide households into having children or not, but also consider the age of children.

Regarding the age groups, no considerable difference in how much food is wasted daily was found between the groups. However, it appeared that the distribution of daily observations got narrower for each age group, indicating a tendency for decreased food waste as age increased. Age as an influencing factor has previously been studied by e.g. Grasso et al. (2019) and Gimenez et al. (2023) who found that an increase in age is associated with a decrease in food waste generation. Even though quantification method and/or sample can be questioned, there seems to be a tendency of households with comparatively older members wasting less, suggesting both that intervention should target younger age groups and that further verification is needed.

Moreover, it was found that, although households with several members wasted more in total, at a per person level, single-person households wasted more and showed a larger span in the distribution of daily food waste. Similar results have been derived from other studies where, for instance, Bilska et al. (2024), Parizeau et al. (2015), and Silvennoinen et al. (2014) all found that average food waste per person decreased with an increase in household members. In a quantitative context, it is important to be aware of household sizes as this will naturally impact the amount of food wasted. To account for this, food waste should be reported as quantity per person and not per household (Wunderlich and Feldman, 2024). However, as the number of household members is likely not static, also this approach of standardization has limitations which can be exemplified by the results of the present study. Looking at the maximum of daily recorded food waste per person, four out of the five households with the comparatively lowest maximum are households consisting of four members or more. On the contrary, out of the five households with the largest maximum daily waste, four are single-person households and one is a two-person household. This may mean that households with more members waste less than those with fewer members, or it could be due to unaccounted guests whose contribution to the waste will have a larger impact in a single household where it is split by one compared to a 4-person household where it would be split by 4. In practice, this could serve an indicator that perhaps the reference unit of *food waste per person per day* is too uncertain, and that it may need to be further disaggregated to e.g. per person per meal where all meal participants are accounted for.

4.3. Limitations and verification

There may be some uncertainties regarding the recorded food waste, such as a few bad images which hindered verification of some extreme events, and non-food or non-organic items being unintentionally included. It should also be noted that no distinction was made between edible and inedible food waste in the study, which otherwise is necessary information for food waste prevention. Although this is information that is possible to obtain from the AQT methodology, it was not included in the aim of this study, but is planned to be examined in future studies. There was also some uncertainty related to non-wasting days, as equipment failure in certain households meant that the number of such days remained unknown in these households. As a result, the main analysis of quantification data was based only on days when food waste had been recorded since overall data availability was limited to these days. Consequently, the presented food waste statistics was likely overestimated, as suggested by results from households where non-wasting days could be accounted for. To better understand the long-term dynamics of household food waste, future studies should account for non-wasting days with greater precision, as overlooking this aspect could significantly impact results.

Nevertheless, the main limitation of the AQT methodology is arguably its inability to capture food wasted into other waste streams. According to Swedish national statistics, food waste from households that enters solid waste streams accounts for 76 % of the total generated food waste where the remaining 24 % constitutes food and liquids that are disposed of into the sewer (SEPA, 2024). This indicates that the AQT would capture roughly three quarters of all food waste generated in households, at least on a general level. However, this is assuming that all solid food waste is discarded in the organic waste bin which may not be realistic. On the other hand, like all member states of the EU, the new legislation introduced in 2024 obliges households to sort out their food waste in Sweden (SFS, 2020:614). With this new legislation, it will be easier to utilize the AQT for future assessments in households where improper sorting has previously been a hindrance.

Aside from the uncertainty or limitation of the quantification method, the general uncertainty of food waste quantification is also associated with statistics, i.e. the sample (Corrado et al., 2019). In this study, the methodological uncertainty can be argued less pronounced than the statistical one, meaning that the food waste quantities would be valid, but their potential to be generalized to a larger population is not. However, this was never the intention of this study since the sample was knowingly restricted from the start, both due to the number of participants and their interest in participation which indicates an awareness within the sample that is larger compared to the general population. To obtain a result that can be scaled up to a population level, a much larger, diversified, and randomized sample is required. Instead, the results should be seen to provide indications to the variations that can be found within and between households, highlighting the importance of recognizing these variations when conducting quantifications.

Although the study sample is not to be considered representative, it is noteworthy how close the overall average daily estimate of 0.159 kg food waste per person is to the Swedish national average, which in 2022 approximated 56 kg per person per year, equaling 0.15 kg per person per day (SEPA, 2024). This could either indicate that the study sample happened to be an accurate representation of the population, or it could be seen as coincidental, therefore raising questions regarding the methodology behind the national statistics as the study sample was likely not representative. It should, however, be noted that in contrast to this study, the national statistics has been adjusted to remove the weight of the paper bags in which the food waste is collected along with flowers, and wrongly sorted items, assumed to account for 16 % of the weight (SEPA, 2024). On the other hand, the 0.15 kg per person per day also includes the estimated amount of food waste discarded in the residual waste bin which has been determined with the help of waste composition analyses conducted by municipalities. It has been shown that in 2022, 28 % of the total food waste ended up in the residual waste (Silva Neira, 2024). Thus, if adding the 16 % of excluded weight while also removing the 28 % assumed to end up in the residual waste, the national average would be approximately 0.13 kg per person per day, which is lower than the average of the present study, or of similar amount if accounting for the non-wasting days.

However, based on their interest in participating in a food waste study, it could be assumed that the participants of this study constitute a group that is more aware than the general population, therefore being more inclined to properly sort their organic waste. Consequently, the degree of properly sorted organic waste would assumingly be higher within the sample compared to the general population, which again would lead to the conclusion that the sample average does not differ notably from the population average. Inevitably, the similarity raises questions surrounding the accuracy of the Swedish national statistics. Considering the extensive effort behind the national statistics, the results of the present study indicate that the uncertainty in statistics (i.e. the sample) may not be a higher limiting factor than the uncertainty of the quantification method, making room to question what method should be used for providing food waste statistics.

5. Conclusions

With the aim to meet the calls for more reliable quantitative assessments of household food waste, this study took use of an automated quantification tool to evaluate the long-term perspective of food waste generation in 28 Swedish households. The results revealed a large variation in generated food waste quantities over time, both between and within households. This variation was found to have further implications on the precision of obtained estimates, suggesting that obtaining an average estimate with a ± 10 % precision would require 115 quantification days at minimum with regards to the present sample. The study also demonstrated that uncertainties of estimates on household food waste are not only associated with how quantification data are collected, but also how they are treated, for instance, when it comes to the attention given to days where no food waste is generated when scaling up results. Even though the sample limited the generalizability of the results, the quantification method facilitated detailed quantification data to be collected which provided insights to both long-term perspectives and demographical characteristics of the sample. The results therefore enable future studies to build on to contribute to a better understanding of the complex issue of household food waste.

Funding

This work was funded by the Swedish Environmental Protection Agency, the Environmental research fund, grant number 2022–00077.

Declaration of competing interest

The authors declare no competing interests.

Data availability

The authors do not have permission to share data.

References

Adelodun, B., Kim, S.H., Choi, K.-S., 2021. Assessment of food waste generation and composition among Korean households using novel sampling and statistical approaches. Waste Manag. 122, 71–80. https://doi.org/10.1016/j.wasman.2021.01.003.

Aitken, J.A., Sprenger, A., Alaybek, B., Mika, G., Hartman, H., Leets, L., Maese, E., Davoodi, T., 2024. Surveys and diaries and scales, oh my! A critical analysis of

household food waste measurement. Sustainability 16 (3), 968. https://doi.org/10.3390/su16030968.
Barker, H., Shaw, P.J., Richards, B., Clegg, Z., Smith, D.M., 2023. Towards sustainable food systems: exploring household food waste by photographic diary in relation to unprocessed, processed and ultra-processed food. Sustainability 15 (3), 2051. https://doi.org/10.3390/su15032051.
Bash AlMaliky, S., AlKhayat, Z., 2012. Kitchen food waste inventory for residential areas in Baghdad City. Mod. Appl. Sci. 6 (8), p45. https://doi.org/10.5539/mas.v6n8p45.
Bilska, B., Tomaszewska, M., Kołożyn-Krajewska, D., 2024. Food waste in polish households – characteristics and sociodemographic determinants on the phenomenon. Nationwide research. Waste Manag. 176, 30–40. https://doi.org/10.1016/j.wasman.2024.01.030.
Casonato, C., García-Herrero, L., Caldeira, C., Sala, S., 2023. What a waste! Evidence of consumer food waste prevention and its effectiveness. Sustain. Prod. Consum. 41, 305–319. https://doi.org/10.1016/j.spc.2023.08.002.
Cattaneo, A., Federighi, G., Vaz, S., 2021. The environmental impact of reducing food loss and waste: a critical assessment. Food Policy 98, 101890. https://doi.org/10.1016/j.foodpol.2020.101890.
Clement, J., Alenčikienė, G., Riipi, I., Starkutė, U., Čepytė, K., Buraitytė, A., Zabulionė, A., Šalaševičienė, A., 2023. Exploring causes and potential solutions for food waste among young consumers. Foods 12 (13), 2570. https://doi.org/10.3390/foods12132570.
Corrado, S., Caldeira, C., Eriksson, M., Hanssen, O.J., Hauser, H.-E., van Holsteijn, F., Liu, G., Östergren, K., Parry, A., Secondi, L., Stenmarck, Å., Sala, S., 2019. Food waste accounting methodologies: challenges, opportunities, and further advancements. Glob. Food Sec. 20, 93–100. https://doi.org/10.1016/j.gfs.2019.01.002.
Cropley, M., Sprajcer, M., Dawson, D., 2022. Wastogram: validation of a new tool to measure household food waste. J. Environ. Psychol. 84, 101896. https://doi.org/10.1016/j.jenvp.2022.101896.
Eičaitė, O., Baležentis, T., 2024. Disentangling the sources and scale of food waste in households: a diary-based analysis in Lithuania. Sustain. Prod. Consum. 46, 195–207. https://doi.org/10.1016/j.spc.2024.02.018.
Elimelech, E., Ayalon, O., Ert, E., 2018. What gets measured gets managed: a new method of measuring household food waste. Waste Manag. 76, 68–81. https://doi.org/10.1016/j.wasman.2018.03.031.
Gimenez, A., Ares, G., Jaeger, S.R., 2023. Exploration of individual factors influencing self-reported household food waste in Australia. J. Sens. Stud. 38 (6), e12881. https://doi.org/10.1111/joss.12881.
Giordano, C., Alboni, F., Falasconi, L., 2019. Quantities, determinants, and awareness of households' food waste in Italy: a comparison between diary and questionnaires quantities'. Sustainability 11 (12), 3381. https://doi.org/10.3390/su11123381.
Grasso, A.C., Olthof, M.R., Boevé, A.J., Van Dooren, C., Lähteenmäki, L., Brouwer, I.A., 2019. Socio-demographic predictors of food waste behavior in Denmark and Spain. Sustainability 11 (12), 3244. https://doi.org/10.3390/su11123244.
Ilakovac, B., Voca, N., Pezo, L., Cerjak, M., 2020. Quantification and determination of household food waste and its relation to sociodemographic characteristics in Croatia. Waste Manag. 102, 231–240. https://doi.org/10.1016/j.wasman.2019.10.042.
Ioannou, A., Georgali, P.-Z., Fokaides, P.A., 2022. Quantification of food waste in an insular island state for all stages of the food supply chain. Resour. Conserv. Recycl. 185, 106486. https://doi.org/10.1016/j.resconrec.2022.106486.
Jansson-Boyd, C.V., Mul, C., Raeva-Beri, D., 2024. Cerebrating and engagement, paths to reduce fresh produce waste within homes. Sci. Rep. 14 (1), 8120. https://doi.org/10.1038/s41598-024-58250-0.
Jones-Garcia, E., Bakalis, S., Flintham, M., 2022. Consumer behaviour and food waste: understanding and mitigating waste with a technology probe. Foods 11 (14), 2048. https://doi.org/10.3390/foods11142048.
KITRO, 2024. KITRO - Simplifying Food Waste Management. https://www.kitro.ch/ [2024-05-27].
Kunsch, H.R., 1989. The jackknife and the bootstrap for general stationary observations. Ann. Stat. 17 (3). https://doi.org/10.1214/aos/1176347265.
Leanpath, 2024. Leanpath Food Waste Prevention Solution. Leanpath Food Waste Prevention Solutions. https://www.leanpath.com/ [2024-05-27].
Leverenz, D., Hafner, G., Moussawel, S., Kranert, M., Goossens, Y., Schmidt, T., 2021. Reducing food waste in hotel kitchens based on self-reported data. Ind. Mark. Manag. 93, 617–627. https://doi.org/10.1016/j.indmarman.2020.08.008.
Lim, V., Bartram, L., Funk, M., Rauterberg, M., 2021. Eco-feedback for food waste reduction in a student residence. Front. Sustain. Food Syst. 5, 658898. https://doi.org/10.3389/fsufs.2021.658898.
Malefors, C., Callewaert, P., Hansson, P.-A., Hartikainen, H., Pietiläinen, O., Strid, I., Strotmann, C., Eriksson, M., 2019. Towards a baseline for food-waste quantification in the hospitality sector—quantities and data processing criteria. Sustainability 11 (13), 3541. https://doi.org/10.3390/su11133541.
Malefors, C., Svensson, E., Eriksson, M., 2024. Automated quantification tool to monitor plate waste in school canteens. Resour. Conserv. Recycl. 200, 107288. https://doi.org/10.1016/j.resconrec.2023.107288.
Parizeau, K., Von Massow, M., Martin, R., 2015. Household-level dynamics of food waste production and related beliefs, attitudes, and behaviours in Guelph, Ontario. Waste Manag. 35, 207–217. https://doi.org/10.1016/j.wasman.2014.09.019.
Quinn, G.P., Keough, M.J., 2010. Experimental design and data analysis for biologists. Repr. with corr., 10. print. Cambridge Univ. Press.
R Core Team, 2023. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. https://www.R-project.org/.
Ramos, G.J., Borges, J.A.R., Domingues, C.H.D.F., Van Herpen, E., 2024. Reducing food waste by simply measuring it: insights from interventions to reduce household food waste. Br. Food J. 126 (2), 812–833. https://doi.org/10.1108/BFJ-02-2023-0092.
Reynolds, C., Goucher, L., Quested, T., Bromley, S., Gillick, S., Wells, V.K., Evans, D., Koh, L., Carlsson Kanyama, A., Katzeff, C., Svenfelt, Å., Jackson, P., 2019. Review: consumption-stage food waste reduction interventions – what works and how to design better interventions. Food Policy 83, 7–27. https://doi.org/10.1016/j.foodpol.2019.01.009.
Roe, B.E., Qi, D., Beyl, R.A., Neubig, K.E., Martin, C.K., Apolzan, J.W., 2020. The validity, time burden, and user satisfaction of the FoodImageTM smartphone app for food waste measurement versus diaries: a randomized crossover trial. Resour. Conserv. Recycl. 160, 104858. https://doi.org/10.1016/j.resconrec.2020.104858.
SEPA, 2024. Livsmedelsavfall i Sverige 2022. Swedish Environmental Protection Agency.
SFS, 2020. 614. Avfallsförordning (2020:614). Ministry of Climate and Enterprise.
Silva Neira, M.J., 2024. Food Waste in Swedish Households - Trends Challenges, and Opportunities towards Achieving the Global Reduction Target (Ms Thesis).. Swedish University of Agricultural Sciences https://stud.epsilon.slu.se/20135/1/silva-m-20240627.pdf [2024-07-16].
Silvennoinen, K., Katajajuuri, J.-M., Hartikainen, H., Heikkilä, L., Reinikainen, A., 2014. Food waste volume and composition in Finnish households. Br. Food J. 116 (6), 1058–1068. https://doi.org/10.1108/BFJ-12-2012-0311.
Stöckli, S., Niklaus, E., Dorn, M., 2018. Call for testing interventions to prevent consumer food waste. Resour. Conserv. Recycl. 136, 445–462. https://doi.org/10.1016/j.resconrec.2018.03.029.
Szabó-Bódi, B., Kasza, G., Szakos, D., 2018. Assessment of household food waste in Hungary. Br. Food J. 120 (3), 625–638. https://doi.org/10.1108/BFJ-04-2017-0255.
UNEP, 2024. Food Waste Index Report 2024. United Nations Environment Programme.
Van Herpen, E., Van Der Lans, I., 2019. A picture says it all? The validity of photograph coding to assess household food waste. Food Qual. Prefer. 75, 71–77. https://doi.org/10.1016/j.foodqual.2019.02.006.
Visschers, V.H.M., Wickli, N., Siegrist, M., 2016. Sorting out food waste behaviour: a survey on the motivators and barriers of self-reported amounts of food waste in households. J. Environ. Psychol. 45, 66–78. https://doi.org/10.1016/j.jenvp.2015.11.007.
Vittuari, M., Garcia Herrero, L., Masotti, M., Iori, E., Caldeira, C., Qian, Z., Bruns, H., Van Herpen, E., Obersteiner, G., Kaptan, G., Liu, G., Mikkelsen, B.E., Swannell, R., Kasza, G., Nohlen, H., Sala, S., 2023. How to reduce consumer food waste at household level: a literature review on drivers and levers for behavioural change. Sustain. Prod. Consum. 38, 104–114. https://doi.org/10.1016/j.spc.2023.03.023.
Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag. https://ggplot2.tidyverse.org.
Withanage, S.V., Dias, G.M., Habib, K., 2021. Review of household food waste quantification methods: focus on composition analysis. J. Clean. Prod. 279, 123722. https://doi.org/10.1016/j.jclepro.2020.123722.
Wunderlich, S.M., Feldman, C.H., 2024. Challenges in the quantification of household food waste: the need for consistent methodologies. Br. Food J. 126 (6), 2539–2547. https://doi.org/10.1108/BFJ-10-2023-0940.
Xue, L., Liu, G., Parfitt, J., Liu, X., Van Herpen, E., Stenmarck, Å., O'Connor, C., Östergren, K., Cheng, S., 2017. Missing food, missing data? A critical review of global food losses and food waste data. Environ. Sci. Technol. 51 (12), 6618–6633. https://doi.org/10.1021/acs.est.7b00401.