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A picture says it all? The validity of photograph coding to assess household food waste

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A R T I C L E I N F O

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A B S T R A C T

Valid measurements are essential in studies into levels of household food waste and differences therein over time, cultures, or consumer groups. They are also key to identifying factors that affect waste levels and to testing the effects of potential interventions. Yet, there is a lack of valid measurement methods for household food waste. The current study assesses the validity of coding of photographs of food waste as a measurement method. In this study, nine coders each estimated 104 food waste instances from photographs, which structurally varied in food amount, food density, size of the container (plate, glass, bowl, pan, etc.) and food category. Comparisons of estimated weights with actual weights show that coders can accurately estimate the weight of food waste from photographs, without general over- or underestimation and with satisfactory correlations with actual weights. Food waste incidences that are more or less difficult to estimate are discussed, as well as differences between coders. Overall, the method appears promising for application in studies examining household food waste levels.

1. Introduction

Food waste is a societal issue with high impact and important policy implications (Schanes, Dobernig, & Gözet, 2018; Secondi, Principato, & Laureti, 2015). Especially in developed countries, a main contributor to overall food waste is the food waste generated by households (Griffin, Sobal, & Lyson, 2009; Xue et al., 2017). Household food waste relates to food management in households, is influenced by consumers' food planning and shopping routines (Stefan, Van Herpen, Tudoran, & Lähteenmäki, 2013), and has implications throughout the supply chain (De Hooge et al., 2017). Hence, food waste is a relevant topic for academics, practitioners, and policy makers interested in consumers' food preferences and the (non)selection of food products. A good understanding of the determinants of household food waste, and of the effectiveness of potential interventions to diminish household food waste, is urgently needed. To obtain such understanding, valid measurements of household food waste amounts are key.

Valid measurements of household food waste are essential to assess levels of waste, to compare these across time, countries, and/or consumer groups, to examine which factors influence the level of food waste, and to test the effects of interventions. Yet, studies using primary data collection to measure household food waste are relatively rare (Xue et al., 2017) and scholars have expressed concern about an apparent lack of valid measures to quantify household food waste (Porpino, 2016). In absence of validated and generally agreed upon measurement methods, prior studies have developed a host of methods, such as food waste diaries (Katajajuuri, Silvennoinen, Hartikainen, Heikkilä, & Reinikainen, 2014; Langley et al., 2010), waste composition analysis (Lebersorger & Schneider, 2011), and various questionnaires (Aschemann-Witzel, Jensen, Jensen, & Kulikovskaja, 2017; Graham-Rowe, Jessop, & Sparks, 2015; Secondi et al., 2015; Stancu, Haugaard, & Lähteenmäki, 2016; Stefan et al., 2013), all with their own advantages and disadvantages (Van Herpen, Van der Lans, Holthuysen, Nijenhuis-de Vries, & Quested, 2018). Our study can be placed in this research line of identifying novel ways to measure food waste (such as, e.g., the "willingness to waste" measure; Wilson, Rickard, Saputo, & Ho, 2017), and attempts to offer and validate a distinct measurement approach.

In their comparison of different measurement methods, Van Herpen et al. (2018) conclude among others that photograph coding is a potentially relevant method to assess household food waste, because of the high correspondence with diary measurements and measurements based on kitchen caddies. Yet, Van Herpen et al. (2018) have only compared photographic coding to other (imperfect) measurements of food waste, and have not assessed the validity of this method by comparing it against objective data (i.e., actual weight). In photograph

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coding, participants are asked to take photographs of their household food waste, and send these to the researcher, who subsequently codes the type and amount of food waste visible on the photographs. Advantages of photograph coding are that it does not rely on consumer memory of food waste incidences, does not require any effort from participants to classify the kind of food waste, and can be applied to a geographically dispersed sample. Photograph coding is relatively effortful for the researcher, however. Given the potential advantages of photographic coding, our research question is:

How valid is photographic coding for the measurement of household food waste?

2. Photograph coding

Prior research has applied photographs of food amounts as aids to increase the accuracy with which people can estimate the amount of food servings (Ovaskainen et al., 2008) and also, more relevant to the current study, to assess portions sizes of consumed meals (Martin et al., 2009, 2014)). In the latter case, participants take photographs of both food selection and plate waste, and coders estimate consumption amounts based on these. In cafeteria settings as well as laboratory and in-home settings, this photography method has been shown to be highly reliable and accurate (Williamson et al., 2003; Martin et al., 2009). Yet, this validation has been restricted to portion sizes and plate waste.

Plate waste is only a small part of total household food waste (Van Geffen, Van Herpen, & Van Trijp, 2017), and foods are wasted before and after preparation. Items such as spoiled fruits or stale bread may be wasted before ever reaching a plate. Leftovers may be discarded after storing these in, for example, plastic containers. In comparison to photographs taken to assess portion sizes, photographs of food waste will vary much more in terms of the stage the food is in (e.g., precooked and leftovers), the amount that is depicted on the photographs (e.g., a full pan of spoiled soup), and the type of containers in which the food is kept (e.g., pans and plastic containers). Hence, there is a need to validate the photograph coding method to foods presented not only on plates but also in various other containers, in various stages of preparation, and to a large range of waste amounts.

The current study aims to validate a standardized way of taking photographs and coding them by comparing estimated with actual weights. In an experiment, the amount and density of the food and the size of the 'container' (glass, plate, pot, or pan that contains the food) are manipulated to obtain diverse instances of food waste. For amount, we expect that photographs with a high amount of food will show more deviation in estimated weight (grams) from actual weight than photographs with a low amount of food, simply because estimates of food-waste amounts have a natural limit (zero grams) and small differences are more easily discernible for small rather than large amounts (cf. just noticeable difference). For density, given that this is difficult to assess on a photograph, we expect that the estimated weight will respond less strongly to differences in density than to differences in amount. This lower response to density should be especially present when food products are visually very similar (e.g., two different types of custard dessert), whereas a larger response in estimated weight should be observed when food products are physically dissimilar (e.g., salad vs. carrots). For container size, prior research (Van Ittersum & Wansink, 2012; Raghubir & Greenleaf, 2006) has shown that the size of a plate, glass or other container can lead to optical illusions whereby volume estimates are systematically biased, even by experts. Our hypotheses are thus:

H1. Estimated weight will deviate more from actual weight in photographs with a high amount of food waste than in photographs with a low amount of food waste.

H2. Estimated weight will respond relatively less strongly to differences in weight than to differences in density.

H3. Volume estimates of the same quantity of food are higher when this food is presented in a small container than in a large container.

3. Method

3.1. Design

The study had a 2 (amount) × 2 (density) × 2 (container size) factorial design, applied to 13 food categories. The categories were chosen based on the top nine categories reported in a study on household food waste across four countries, which together contained 79.4% of total household food waste (Van Geffen et al., 2017). Appendix A provides an example of photographs that were used. To manipulate amount, we created small (few spoons, bread crusts, etc.) versus large (single-serving size, several slices of bread, etc.) amounts of food. To manipulate density, we used different types of products within the same categories, such as carrots versus lettuce for raw vegetables. To assess effects of container size, we structurally put food into either relatively small or large containers (plates, pans, etc.). The resulting categories, products, and containers are provided in Appendix B. Because the photographs of the mixed meals contained 3 food items, which were separately coded, this led to 88 (8 × 11) separate photographs of 104 food waste items (8 × 13 foods). The food items in the photographs were carefully weighed.

The food items were photographed after being placed on a placemat with a checked pattern to enable coders to assess size relatively easily (cf. Van Herpen et al., 2018). This resembles conditions in which studies on household food waste are likely to take place, as providing households with a checked placemat would be relatively easy (e.g., placemats could be send by regular mail or provided as a printable document). Providing households with other devices, such as standard containers in which food waste could be photographs, would provide a much larger challenge both logistically and budgetary for the researcher, and would increase the effort required from participants. Hence, containers were varied as part of the study design.

3.2. Coders

Ten coders, who were unfamiliar with the study design, independently estimated the weight of each of the food items on the photographs. Coders were undergraduate students at a Dutch university. Because one of the coders did not adhere to instructions concerning the order in which photographs were to be coded, we analysed results of the remaining nine coders. Coders received a monetary payment for their effort, and a prize (box of chocolates) was awarded to the coder whose total estimated weight was closest to the actual total weight.

3.3. Coding process

The coders all received a different order in which they had to code the photographs. Order was constructed such that food categories, amount, density, and container size were dispersed over the sequence (i.e., no coder coded photographs of food from the same category immediately following each other). Coders were instructed to not look back at previously coded photographs to prevent them from directly comparing photographs that resembled each other. This prevented coders from directly comparing photographs which differ only on one factor (e.g., only on container size), as this is something that would not occur in studies on actual household food waste. Coders noted the

Table 1
Descriptive measures of actual and estimated weights (in grams).

		Estimated weight			
Measure	Actual weight	Minimum estimated	Maximum estimated	Mean of the estimates	SD
Mean weight	123	78	181	118	27
Total weight	12,774	8,144	18,841	12,246	2,811
Manipulated factor					
Amount					
Large	210	130	308	198	48
Small	36	27	55	38	9
Density					
High	144	91	230	131	40
Low	102	65	132	105	18
Container size					
Large	123	66	164	103	27
Small	123	90	198	132	29
Product category					
Vegetables (mixed meal)	75	45	99	69	20
Potatoes (mixed meal)	120	75	264	132	63
Meat (mixed meal)	55	55	137	73	25
Potatoes	82	53	217	125	47
Fruit	108	71	104	82	12
Leftover pasta	119	53	219	109	48
Pasta in pan	134	60	223	103	47
Bread on plate	34	27	44	32	6
Bread (loaf)	243	200	260	235	40
Soup	432	133	681	343	165
Dessert	70	26	121	57	27
Liquids	99	68	282	134	64
Raw vegetables	27	22	55	38	13

estimated weight of the food in grams. On the coding form, they could also note how they arrived at their estimate.

Before starting the coding process, coders received a joint training session. During this session, they coded four photographs of actual food waste, selected from a pilot study. Actual weight of the wasted food was not provided to the coders. Coders were instructed that they could use all resources that they wished and were encouraged to find weight measurements for food items online as reference points throughout the coding process. This training ensured that coders understood the coding task, without increasing accuracy in coding itself. By allowing coders to use different resources, we obtain conservative estimates of reliability, and prevent that the use of one specific standard leads to extreme estimates of validity.

4. Results

4.1. Coders' use of resources

One of the coders reported using only her own knowledge of product weights when making the estimates. All other coders reported using online resources, in addition to relying on their own knowledge. Two of the coders also weighed products themselves to obtain good estimates.

4.2. Differences in actual food weight

Before examining the validity of the weight estimates, we first examined the variation in actual objective weights (see Table 1). Actual weight differed between 4 and 822 g, with an average of 123 g (SD = 165). We ran an analysis of variance (ANOVA) to investigate the effect of amount, density, and category on actual weight, including the main and two-way interaction effects. Container size was not included, because that factor was manipulated without changing actual weight. Please note that additionally including the three-way interaction is not possible as no degrees of freedom would be left for the error term. As expected because of the way in which we constructed the food-waste portions, results showed strong main effects of amount ($F(1, 64) = 7778.18$, $p < .001$, $\eta_p^2 = .99$) and category ($F(12, 64) = 923.58$, $p < .001$, $\eta_p^2 = .99$) as well as density ($F(1, 64) = 456.23$, $p < .001$, $\eta_p^2 = .88$). Additionally, all two-way interaction effects were significant (all $Fs > 8.08$, $ps < 0.001$). Thus, the effect of density depended on product category (which is a result of our decision to sample foods in relatively high or low density within each category) and so did the effect of amount (similarly a result of our decision to use amounts that are relevant for the category). Moreover, the effect of density depended on amount, with density having a stronger effect when amount was large (which is the result of the fact that weight is a function of density times amount).

4.3. Validity of weight estimates

As a first assessment of the validity of the weight measures, we examined descriptive measures of actual and estimated weights (see Table 1). From the table it is apparent that on average the coders were quite accurate, but individual estimates could diverge considerably from the actual weights. As shown in Fig. 1, two of the coders tended to provide estimates that were either considerably lower or higher than the other coders (and than the actual weight). Formal tests of the difference scores (actual minus estimated weights) confirmed that Coder 8 structurally underestimated ($t(103) = 3.86$, $p < .001$) whereas Coder 9 structurally overestimated ($t(103) = -3.06$, $p = .003$) waste amounts. For the remaining six coders, the difference scores were not

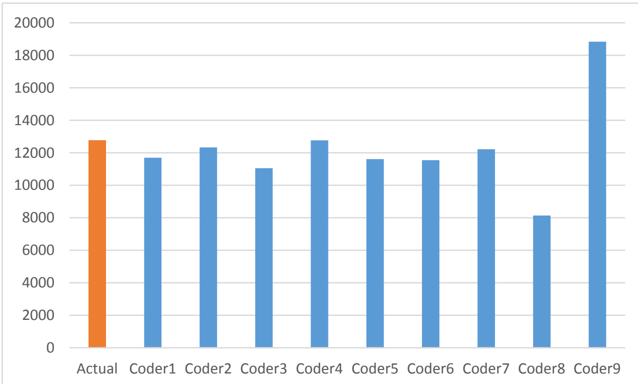

Fig. 1. Total actual and estimated weights in grams.

significantly different from zero, and we thus found no evidence of over- or underestimation. It was also apparent that large amounts had more variance in the estimates than small amounts, as expected.

Next, Pearson correlations between the estimates from each coder and actual weight, and between the nine individual coders, were calculated. The correlation between the coders and the actual weight was good (r between .58 and .88, with an average of .78), indicating that, overall, coders were able to assess relative actual weight well. The correlation between coders (interrater reliability) was also good (r between .50 and .94, with an average of .73).

Subsequent multi-level models, with measurements nested in coders, further assessed the estimated weights. A null-model showed a very low intraclass correlation coefficient (ICC) of .01, which indicates that relatively little variance is due to differences in coders' mean estimates across all photographs. Table 2 provides tests for the effects of the manipulations and all two-way and three-way interactions on estimated weights (four-way interaction not taken up). To obtain a valid measurement, weight estimates should depend on volume and density, and differ across product categories. Moreover, weight estimates should not depend on container size. Results showed that all main effects were significant, and their patterns were in line with expectations (see Table 1 for means). Thus, weight estimates were higher for high-density than for low-density foods, for large than for small amounts, and for small than for large containers.

Pairwise comparisons were used to further examine the interaction effects. Container size should not affect weight estimates, and for most categories and amounts the effects of container size were indeed not significant. Container size only significantly affected weight estimates for the large amounts of soups (mean difference = 421.7; $p < .001$) and marginally for the large amount of potatoes (mean difference = 69.2, $p = .055$; not significant after Bonferroni correction). In all other cases, effects of container size were not significant ($ps > .2$).

Food density, which should affect estimates, did not affect weight estimates of small amounts ($p = .315$), but had a significant effect on weight estimates of large amounts ($p < .001$). Examining the effects of density across the different food categories showed that density had effects for liquids, soup ($ps < .03$), and both types of potatoes (mixed meal component and separate; these effects are not significant after Bonferroni correction though), but not for the other categories ($ps > .2$). Partly this may be because differences between foods with low and high density were hard to distinguish in the photographs, but some of the categories in which effects of density were not significant did contain clearly distinguishable foods (e.g., carrots vs. lettuce for raw vegetables).

Effects of amounts were significant for most categories ($ps < .002$), with exceptions for bread on a plate ($p = .539$) and raw vegetables ($p = .207$). Also, coders' estimates of desserts in large bowls did not significantly differ between small and large amounts ($p = .110$). Apparently, coders experienced difficulties in estimating the weight differences between large and small amounts in these specific cases.

4.4. Under- and overestimation

Next, we examined the difference scores (actual minus estimated weights), to assess whether there was systematic over- or underestimation of the weights. Results showed that this was not the case (intercept not significant, see Table 2). As shown in Table 2, there were significant effects of density, amount, container size, and category, as well as several interactions. Coders tended to underestimate foods with high density ($M_{diff.score} = 13.19$) and slightly overestimate food with low density ($M_{diff.score} = -3.04$). They also underestimated foods in large amounts ($M_{diff.score} = 12.08$; due to a severe underestimation of soups in large pans, with $M_{diff.score} = 167.39$), but not those in small amounts ($M_{diff.score} = -1.94$). Finally, they underestimated foods in

Table 2
Multi-level model output.

Effect	df	Estimated weight		Difference[1]		Absolute difference		Proportion[2]	
		F-value	*p*	*F*-value	*p*	*F*-value	*p*	*F*-value	*p*
Intercept	1, 8	170.8	< .001	0.3	.589	148.8	< .001	202.8	< .001
Density	1, 848	13.4	< .001	5.3	.021	1.9	.170	76.6	< .001
Amount	1, 848	510.8	< .001	4.0	.047	283.2	< .001	7.6	.006
Container size	1, 848	16.5	< .001	16.5	< .001	2.2	.139	11.2	.001
Category	12, 848	45.4	< .001	6.9	< .001	53.5	< .001	17.0	< .001
Density * amount	1, 848	5.1	.024	2.8	.093	0.6	.431	0.3	.601
Density * c.size	1, 848	0.0	.994	0.0	.994	2.7	.099	0.2	.662
Density * category	12, 848	3.2	< .001	3.3	< .001	2.6	.002	8.2	< .001
Amount * c.size	1, 848	9.4	.002	9.5	.002	1.7	.197	1.3	.258
Amount * category	12, 848	33.0	< .001	5.3	< .001	37.2	< .001	10.0	< .001
C.size * category	12, 848	5.7	< .001	5.8	< .001	3.4	< .001	2.9	.001
Density * amount * c.size	1, 848	0.0	.956	0.0	.956	1.7	.192	0.3	.580
Amount * c.size * category	12, 848	4.4	< .001	4.4	< .001	2.5	.003	2.1	.012
Density * c.size * category	12, 848	0.3	.982	0.3	.981	0.8	.693	1.2	.249

[1] Difference score calculated as actual weight minus estimated weight.
[2] Proportion calculated as estimated weight divided by actual weight.

large containers ($M_{diff.score}$ = 19.39) and overestimated those in small containers ($M_{diff.score}$ = −9.24). These effects were attenuated by product category differences. Generally, most food categories were underestimated ($M_{diff.score}$ between 2.23 (bread on plate) and 89.44 (soups)), but liquids ($M_{diff.score}$ = −35.08), meat ($M_{diff.score}$ = −17.60), raw vegetables ($M_{diff.score}$ = −11.40) and potatoes ($M_{diff.score}$ = −43.24) were overestimated.

4.5. Accuracy

In a separate multilevel model, we examined the absolute difference between actual and estimated weights, as a way to identify when estimated weight deviated most from actual weight, that is, when coding weights was most difficult. Results showed significant main effects of amount and category (see Table 2). Estimated weights deviated more from actual weights for larger amounts ($M_{abs.diff}$ = 94.51) than for small amounts ($M_{abs.diff}$ = 18.17), indicating that, as expected, large amounts were more difficult to estimate accurately than small amounts. Regarding the differences between food category, what mainly stood out was that the soup in a pan had relatively high absolute differences between actual and estimated weights ($M_{abs.diff}$ = 249.75 for soups; other categories ranged between 8.04 (bread on plate) to 67.71 (potatoes from mixed meal). The soups in pans were thus the most difficult to estimate.

4.6. Proportions

Finally, proportional weight under-/overestimation was examined, by a multilevel model on the ratios of estimated versus actual weights. Proportional weight under-/overestimation is relevant because the same total food-waste amount could be reported in one single photo (e.g., waste from multiple plates scraped together), but also in multiple photos, each showing a part of the total amount (e.g., on individual plates). Results showed significant main effects, such that relative overestimation was higher for small than large amounts (M_{small} = 1.26 vs. M_{large} = 1.13), for low than for high density (M_{low} = 1.41 vs. M_{high} = 0.99), and for small than for large containers (M_{small} = 1.28 vs. M_{large} = 1.12). This implied that presenting food as a large amount (i.e., piling food waste together for a single photo) and in a large container would lead to more accurate measurements than using separate photos of smaller amounts or using smaller containers. These main effects could be further qualified by significant interactions with product category, which indicated that these effects were present for only some of the categories.

4.7. Differences between coders

ANOVAs assessed the effects of the manipulations on estimated weights for each of the coders separately, including main effects as well as all two-way and three-way interactions in the models. Results showed that one of the coders did not respond to differences in density (all main and interaction effects with density not significant). Moreover, two of the coders did not respond to differences in container size, which should positively affect estimation accuracy. Thus, although the multilevel model showed that very little of the overall variance was due to differences between coders, there still were relevant differences.

5. Discussion

The current study has compared estimated weights of photographed food waste to actual weights, to assess the validity of photograph coding as a measurement instrument for household food waste levels. This extends prior research in which photographs of portion sizes and plate waste have been validated (Williamson et al., 2003; Martin et al., 2009). In line with this prior research, results indicate that coders are well able to estimate weights of food waste from photographs: (1) most of the coders do not systematically over- or underestimate the amount of food waste, (2) correlations between estimated and actual waste are high, (3) changes in container sizes, which should not affect estimates, generally indeed did not affect estimates with the exception of two food categories, (4) density, which is difficult to assess from photographs, nonetheless affected weight estimates when large amounts of food waste were shown, and (5) coders generally responded to differences between small and large amounts, with the exception of a few food categories. Thus, it appears that photographic coding is a valid and promising method for household food waste assessment.

Modelling results have indicated that the variance in the dataset is primarily due to differences between the photographed food waste instances. Yet, relevant differences between coders have still appeared. In our case, one coder systematically underestimated amounts whereas another coder systematically overestimated. Moreover, coders differ in whether they are able to pick up differences in food density, and whether they (incorrectly) respond to differences in container size. This implies that the common practice of using multiple coders is advisable, to attenuate the potential effects of divergent estimates. It also implies that training of coders, as has been applied in studies on photographic coding of portions sizes (Martin et al., 2009), may improve the accuracy of estimates.

There are differences between the food waste instances in how accurate the coders could assess food waste. The photographs of soups in large pans are especially difficult to estimate. Additionally, the lack of effect of density on estimates of food weight for many product categories shows that density can be difficult to assess with only visual information. Moreover, foods in large containers tend to get underestimated and foods in large amounts are more difficult to estimate than foods in small amounts. Training of coders could focus on these cases.

The results for proportions moreover showed that overestimation is relatively higher for small than for large amounts. When participants in a study provide photographs of food waste, they could be instructed to photograph similar waste (e.g., plate waste from multiple plates) as a single large portion. This should lead to more accurate coding than multiple photographs of smaller individual portions.

With respect to differences across categories, we find that most food categories are underestimated, and this should be taken into consideration when interpreting results from photograph coding. Exceptions are liquids, meat, raw vegetables, and potatoes, which in our study are overestimated.

5.1. Limitations and future research

Our study has several limitations that should be kept in mind. First, as any study, ours is limited in the stimuli that are used. Food waste can occur in many categories, for foods in many different forms and shapes, and in many different containers. Future research could extend upon the current study by examining other types of categories, amounts, and containers. In specific, future research could examine composite foods (e.g., salads composed of multiple ingredients), which have not been included in the current study.

The current study has examined relatively naive coders, who have not received any prior training based on accuracy of the estimates. Results show that even such naive coders can provide valid estimates. This is a conservative assessment of the validity and reliability of photographic coding of food waste. Future research could assess the extent to which training improves the validity and accuracy of food waste estimates, especially since professional companies with trained coders may be used if this measurement becomes more established. Next to training, extension of the tools available to the coders could be helpful as well. In addition to the online resources that our coders relied upon, standard photographs of various portions of food from diverse categories and in diverse containers, with associated actual weights, could potentially be useful. This would require an expansion of existing databases with standard portion photographs used for food intake measurement (Martin et al., 2009, 2014)).

Furthermore, although the coders in our study are untrained, the photographs provide them with help in estimating sized through the use of placemats with a checked pattern. Because such placemats have been used in prior research (Van Herpen et al., 2018) and should be relatively easy to include into studies in which household members are asked to make photographs of food waste, we feel that this aid is realistic for studies on household food waste. Yet, future research may assess the usefulness of such a placemat, and the extent to which it improves the accuracy of food waste estimates.

5.2. Conclusion

Nowadays, making photographs of food items (and sharing these using social media) has become commonplace. It should thus be relatively easy to entice people to consistently photograph their food waste and send in the photographs, given the widespread availability of smart phones and internet access. As our study shows that coding of such photographs can provide valid measures, this research method appears promising for application in studies examining household food waste.

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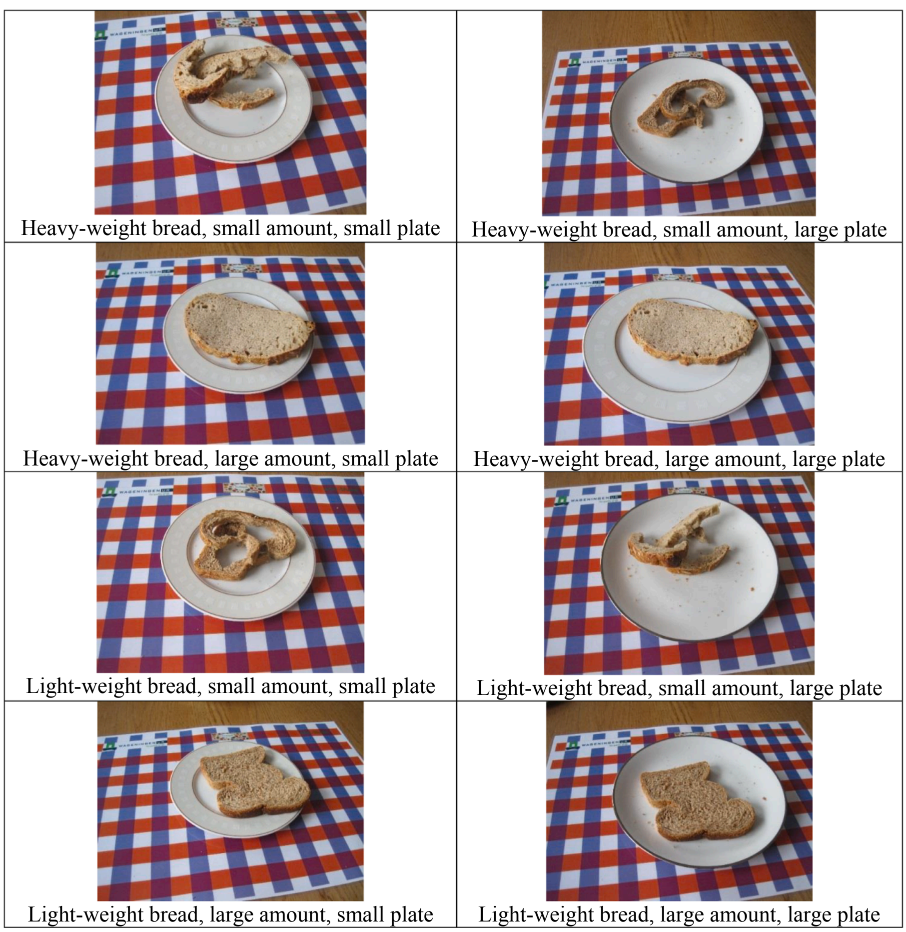
A. Appendix

See: Appendix A



Appendix A. Example photographs (Bread on plate).

B. Appendix

See: Appendix B

Appendix B
Product categories, products, and containers.

Product category	Low density food	High density food	Container	Small amount	Large amount
Vegetables (mixed meal)	Mushroom	Broccoli	Plate	About two spoons	Single serving size
Potatoes (mixed meal)	Parisian potatoes	Cooked potatoes	Plate	About three spoons	Single serving size
Meat (mixed meal)	Meat replacement	Steak	Plate	Single bite-size	Single serving size
Potatoes	Sautéed potatoes	Cooked potatoes	Plate	About four spoons	Single serving size
Fruit	Peach	Pear	Glass bowl	Quarter piece	One whole item
Leftover pasta	Lumachine	Spaghetti	Plastic storage box	Quarter serving size	Three quarter serving size
Pasta in pan	Lumachine	Spaghetti	Pan	About two spoons	Single serving size
Bread on plate	Light-weight bread	Heavy-weight bread	Plate	Crust of one slice	One slice
Bread (loaf)	Light-weight bread	Heavy-weight bread	Bread basket	Two slices	Twelve slices
Soup	Bouillon	Pie/potato soup	Pan	A few spoons	About four serving sizes
Dessert	Fluffy whipped custard	Custard with cream	Dessert bowl	About one spoon	Single serving size
Liquids	Drink bouillon	Milk	Glass	About four sips	Single serving size
Raw vegetables	Lettuce	Carrots	Plastic bowl	About two spoons	Single serving size

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