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Buy Three to Waste One? How Real-World Purchase Data Predict Groups of Food Wasters

Sybilla Merian [1,*], Sabrina Stöeckli [1,2], Klaus Ludwig Fuchs [3] and Martin Natter [1]

[1] Department of Business Administration, Chair of Marketing, University of Zurich, 8032 Zurich, Switzerland
[2] Department Consumer Behavior, Institute of Marketing and Management, University of Bern, 3012 Bern, Switzerland
[3] Department of Management, Technology and Economics (D-MTEC), ETH Zurich, 8092 Zurich, Switzerland
* Correspondence: sybilla.merian@business.uzh.ch; Tel.: +41-44-634-29-96

Abstract: Approximately one-third of all food produced for human consumption is either lost or wasted. Given the central position of retailers in the supply chain, they have the potential to effectively reduce consumer food waste by implementing targeted interventions. To do so, however, they should target distinct consumer groups. In this research, we use a unique data set comprising the grocery shopping data of customers who use loyalty cards, complemented with food waste reports, to derive three distinct target groups: *traditionals*, *time-constrained*, and *convenience lovers*. Based on the general behavioral change literature, we discuss diverse target group-specific interventions that retailers can implement to reduce consumer food waste. Overall, we pave a research path to examine how retailers and marketing can effectively shift consumer behavior toward more sustainable food and shopping practices and assume responsibility within the food supply chain.

Keywords: food waste; retailer; segmentation; behavior change intervention

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1. Introduction

Reducing food waste is one of the core strategies in meeting the United Nations (UN) Sustainable Development Goal (SDG) of mitigating climate change [1]. Globally, roughly one-third of all food produced for human consumption is lost or wasted every year. This corresponds to 30% of the world's agricultural land, 20% of fresh water, and roughly 8% of anthropogenic greenhouse gas emissions [2]. While food waste in lower-income regions occurs predominantly in the earlier stages of the food supply chain, consumers are the single biggest contributors to food waste in higher-income regions [1,3]. The closer the food waste is to the consumer's plate, the higher the accumulated environmental impact [4], thereby emphasizing the need for effective consumer-level interventions. In this research, we explore and discuss the potential levers that retailers can deploy in implementing consumer-specific interventions to reduce food waste.

Due to the central position of retailers in the supply chain, they have the potential to significantly contribute to food waste reduction [4]. Although they are only responsible for a comparably low share of food waste, they indirectly contribute to waste at other stages of the food supply chain [5–7]. In fact, common marketing practices such as the pricing of products [8,9], their placement within the store [9], ensuring high aesthetical standards [10], providing a large variety of products at any time of the day and year [11], as well as distribution agreements [12,13] were recognized as drivers of food waste. Given the recent shift in consumers' values toward higher levels of sustainability [14], such practices are increasingly criticized in the public debate. Consequently, retailers are pressured more than ever to make consumption more sustainable [5].

Apart from the ability to change classical marketing measures [15], retailers have additional levers that can significantly reduce food waste at the consumer level which have not gained much attention. First, they have many interaction points with their customers (e.g., points of sale, online shop, loyalty program, advertisements, social media, and mobile applications) and, thus, have many opportunities to implement interventions aimed at reducing food waste [16]. Second, retailers have been capturing large-scale data sets on real-world purchase behavior (e.g., shopping frequency), which they are yet to leverage in the mitigation of food waste. They can usually associate such data with specific consumers (e.g., through loyalty program or online shopping accounts) or consumer groups (e.g., consumers in a specific neighborhood). Combined with retailers' skills of segmenting customers and targeting them with tailored marketing measures, we argue that retailers have a potentially decisive role in mitigating consumers' food waste by implementing effective consumer-specific interventions [17–19].

In contrast to traditional, usually generic, one-size-fits-all interventions, targeted interventions are far more effective in changing consumer practices [20]. Interventions aimed at consumers who do not intentionally plan their grocery purchases via a shopping list can only be reached via generic, normative messaging. However, consumers who are characterized by the personal norm and intention to use a shopping list benefit more from tips that strengthen their action planning toward building habits (e.g., asking family members when they will be absent during the week). A prerequisite for targeted interventions is a comprehensive understanding of the target group's attitudes, norms, feelings, and habits [21]. Here, a typology of distinct consumer food waste segments is informative for the design and implementation of targeted interventions that effectively reduce food waste.

Researchers have repeatedly identified distinct consumer food waste segments. A study involving consumers in five Northern and Western European countries, for instance, found five food waste types: the (1) *well-planning cook and frugal food avoider*, (2) *young foodies*, (3) *established*, (4) *uninvolved young male wasters*, and (5) *convenience and price-oriented low income wasters* [22]. A study in Turkey found four types of food wasters: (1) *conservers*, (2) *considerates*, (3) *reluctants*, and (4) *prodigals* [23]. An Irish study found two distinct types: (1) *uncaring* and (2) *caring consumers* [1]. Despite the need for evidence-based clusters for the generation of tailored interventions, existing segmentations have several drawbacks. First, they differ considerably in their methods, such as sample, descriptor variables, and clustering algorithms. One commonality of existing segmentations is their focus on self-reported variables. While this has the advantage of providing comprehensive insight into consumers' psychology, it has at least two disadvantages. First, the focus is on psychological constructs that are usually not directly observable, making it difficult to target segments. Although segments are often described by diverse socio-demographics such as gender and household size, these descriptors have limited use in segment-specific communication. The second disadvantage is that there is usually a discrepancy between actual behavior and self-reported intentions, attitudes, and emotions. Meta-analyses have shown, for instance, that intention only explains about 30% of the variance of actual behavior [24,25]. One explanation is that many self-reported measures demand reflection and introspection and, thus, involve evaluative and cognitive processes that tend to be affected by influences unrelated to the measured construct. Items such as "I think food waste is unnecessary", for example, are likely to be affected by social desirability and impression management [26]. We argue that retailers are in an ideal position to address the two disadvantages: They possess large-scale data of real-world purchase behavior that can be used for customer segmentation. Furthermore, they can often link segmentation data and actual consumption records to their customers or customer groups, targeting them with tailored and relevant interventions that offer superior potential compared to the current, generic, one-size-fits-all campaigns.

To understand consumers in terms of their food waste behavior and derive evidence-based and tailored interventions, there is another important aspect: the definition of meaningful segmentation and descriptor variables. Specifically, segments should be maximally different in terms of their food waste patterns and described through variables focused on observable factors that can be used to identify and address the corresponding consumers. Based on previous research and the purchase data that are commonly available to retailers, we identify at least nine important predictors of food waste: (1) *discount orientation* [27], that is, the extent to which consumers get price, date, and quantity discounts or use coupons; (2) *shopping frequency* [28], that is, the frequency with which consumers purchase food; (3) *planned shopping* [29], that is, the extent to which consumers have steady patterns of routine shopping; (4) *overprovisioning* [30,31], that is, the extent to which consumers buy too much, for example, because they show "caregiver" patterns; (5) *sustainable behavior*, that is, the extent to which consumers buy organic, regional, and social food; and (6) *shopping involvement* [18], that is, the extent to which consumers buy producer labels or shop on weekends [17]. Further, we look at variables that indicate customer loyalty as this will likely influence the effectiveness of interventions: (7) *shopping regularity* [19], that is, the extent to which consumers do their purchases on a regular basis; and (8) *monetary value*, that is, the extent to which consumers' willingness and ability to spend might influence their buying decisions [32,33]. Overall, we argue that these variables are particularly meaningful for retailers to consider in their segmentation efforts. Table 1 provides an overview of the existing research and the operationalization of the different predictors.

Table 1. Overview of literature about predictors for segmentation.

Predictors	**Literature**	**Operationalization**
Discount orientation (1)	There are mixed findings regarding the influence of discounts on food waste (see [27] for an overview).	We used the share of different kinds of discounts (straight price discounts, multi-packages, price-reduced multi-packages, and expiry-date-related discounts) and the number of coupons (general or food-category/product-specific) used per trip as indicators of a discount orientation. This distinction is very interesting as the existing literature on the association between different kinds of discounts and food waste is fragmented. Some studies differentiate between sole price discounts and multibuys [8], whereas others only look at subdimensions or do not clearly distinguish between them [34,35]. By including different kinds of discounts as well as coupons, we contribute to a better understanding of the relationship between food waste and discounts.
Shopping frequency (2)	Shopping frequency is related to food waste. A better day-to-day management of food as a result of frequent purchases could be outweighed by being more exposed to in-store temptations [34]. Some studies have also found that less frequent shopping was associated with more food waste [28].	We used the average inter-purchase time of all food categories (fruits, veggies and salads, bread, dairy products, meat and fish, meals, sweets and snacks) as indicators of shopping frequency.

Table 1. *Cont.*

Predictors	Literature	Operationalization
Planned shopping (3)	Planning behaviors such as meal planning or inventory checks prior to the grocery run were associated with less food waste [29,34]. It was proposed that planning reduces the amount of surplus foods/unplanned purchases [36,37].	To operationalize different dimensions of routine shopping and planning, we used the average number of bags purchased per trip, the average time between shopping trips (referred to as average inter-purchase time), and the variance of the basket size. We assumed that a high number of bags purchased was associated with unplanned purchases as consumers either did not bring their bags or bought more than intended. Going to the store less frequently was associated with more unplanned purchases as the goal of the purchase was more abstract [38]. We also assumed that the variance in the basket size was associated with routine shopping/planning. Low variances could either mean that people always bought the same number of products or typically bought low amounts of products, both indicators of concrete shopping goals and, therefore, fewer unplanned purchases [38].
Overprovisioning (4)	Buying too much was recognized as a direct cause of food waste [36].	We used the amount of kilo calories purchased per household member and day as well as the number of kids (as a proxy for a good provider identity [30]) and the share of meals eaten outside [32,39] as indicators of overprovisioning.
Sustainable behavior (5)	An aspect that has not gained much attention in the literature on food waste is how sustainable purchase practices relate to food waste.	We used the share of organic, fairtrade, regional, and pseudo-sustainable products (products labeled as sustainable but without a specific standard, mostly plant-based convenience food) as indicators of sustainable behavior.
Shopping involvement (6)	While Le Borgne et al. [18] found that involvement in a specific category was related to a lower perceived probability of waste, involvement in shopping has not gained much attention.	We used the share of private and producer labels and shopping trips made on weekends (both absolute and weighted by the number of products purchased) as indicators of shopping involvement as previous research found that individuals who are more involved in grocery shopping are more likely to shop on weekends and that they prefer brand names over generic [17].
Shopping regularity (7)	It was argued that buying food at relatively fixed intervals could contribute to food waste [39].	We used the standard deviation of the inter-purchase time as a predictor of shopping regularity.
Monetary value (8)	A lower valued basket was previously associated with less food waste [33] but also with more organic food waste [32]	We used the monetary value spent per day and person as a proxy for the total monetary value.

This research contributes to the existing literature in three ways. First, no study has previously examined retailers' potential in tailoring consumer food waste interventions based on actual purchase behavior. We narrow this gap by using a unique data set consisting of digital grocery receipts from two major retailers in a European country and self-reported food waste measures. Due to the weaknesses of self-reported food waste measures (e.g., limited predictive power for actual food waste [40]), we also conducted a validation study where we collected and analyzed actual food waste information from 40 households. Second, we operationalize different aspects that have previously been associated with food waste (e.g., the shopping frequency [28,34,41,42]) based on real-world purchase data instead of self-reported measures. Using observed (vs. self-reported) behavior has advantages in explaining and predicting future behavior as it reflects actual behavior better [24,25]. Last, by computing cluster-wise regressions, we identified household segments that differed in their relationship between purchase and food waste behaviors. Based on this, we discussed a set of diverse target group-specific interventions. In doing so, we built a basis for practitioners (i.e., retailers) interested in directing their strategy toward sustainability and responsibility. In addition, by looking at different groups of wasters, we contribute to existing food waste literature by emphasizing the significance of household/individual differences regarding food waste [43]. In sum, this research focuses on identifying consumer segments that differ in their food waste behavior and discusses concepts from the behavior change literature aimed at implementing effective interventions toward reducing consumer food waste. This approach can also be used as a basis for other sustainability-related challenges such as reducing meat or plastic consumption.

This paper is structured as follows: In the methodology section, we describe the measures and statistical model used to analyze the data. Thereafter, we present the resulting clusters of the model. In the last section, we discuss our results and present some insights for potential interventions.

2. Materials and Methods

2.1. Material

2.1.1. Food Waste Self-Reports

To capture the households' food waste behavior, we used a battery of category-specific self-reports capturing food waste shares. This battery contained the households' food waste relative to the total weight of the food bought [44,45]. Self-reported food waste was measured through the following instruction:

"How much of the following food items does your household NOT CONSUME, this means give away to non-household members or throw away as food waste (in %)?"* *neighbors, friends, elderly, pets" [46]. Note that we provided the households with a list of seven food categories (e.g., fruits, vegetables, bread, dairy products, and eggs) and asked them to estimate a separate percentage for all categories on a six-point scale from 0 to 100% (1 $\leq$ 10%; 2 = 10–20%; 3 = 20–40%; 4 = 40–60%; 5 = 60–80%; 6 = 80–100%).

2.1.2. Actual Food Waste Behavior

To ensure the validity of our dependent variables, we conducted an additional validation study, where we collected and measured the food waste of 40 households (average household size = 2.45; average number of kids = 0.125; annual income = 3.17) over one week and compared these measurements with self-reported measures of food waste (same questionnaire as in our main study). Participants were recruited through our personal network in both rural as well as urban areas and had to be willing to share their paper-based receipts with us. Besides filling in a survey and providing us with all paper-based receipts, the participating households were asked to collect their waste in bags provided by us. After one week, the waste was collected, weighed, and documented. Compared to existing studies with similar designs [47], the participants were not actively informed in detail about the purpose of the study. They were told that the study was about waste flows and how these could be optimized. This procedure was approved by the ethics committee (OEC IRB #2020-028, 26 May 2020). Please note, the data from these 40 households were not used for our cluster analyses described below. The study took place in two waves, in June and October 2020.

The results of the validation study revealed a highly significant positive correlation between the reported and measured shares of food waste ($r = 0.35$, $p < 0.001$). We only included observations (reported categories per household) where food was wasted. Therefore, we found a high positive correlation between the frequencies of the measured and reported shares ($r = 0.97$, $p < 0.001$). As Figure 1 shows, the distributions of the measured and reported shares were very similar. We found that the sample underreported by an average of 0.5%. Overall, we conclude that our food waste self-reports were a good proxy for actual food waste behavior and, therefore, were used for further analysis.

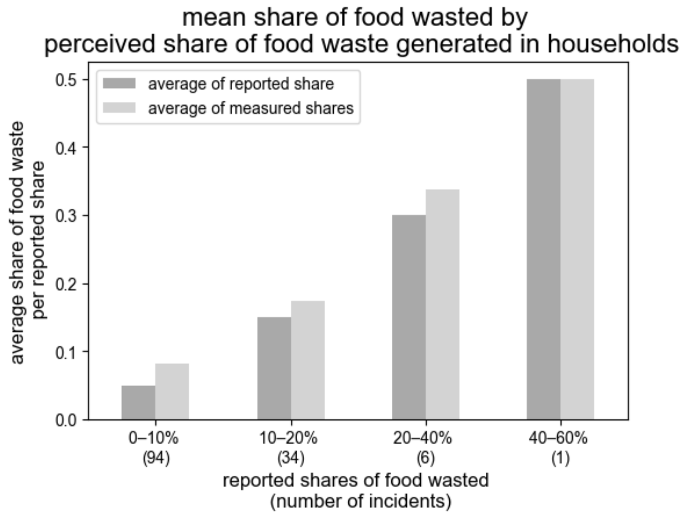

Figure 1. Comparison of reported and measured shares.

2.1.3. Digital Purchase Data

To capture the purchase patterns, we used the households' historic purchase data. Being part of the retailer's loyalty program allowed the households to use the customer card or app for payment of purchases, thereby creating a record for every item purchased (name of retailer and webpage of customer's card were blinded for the review process). The customers could access and download (in CSV form) their data online. The data provided timestamped information about which products (product names) had been bought over the previous two years. Based on our product database containing approximately 6472 products, we enriched the households' purchase data from the last half year with product information (e.g., weight, unit, pricing, food category, and nutritional composition).

2.1.4. Food Waste Intention and Behaviors

In the second part of the survey, after collecting the food waste self-reports, we further collected self-reported measures on the intention to reduce food and behaviors that were previously associated with discarding food (e.g., producing leftovers, grocery planning, overprovisioning, storing, preparation, and assessing the edibility of the food [48]). All 13 items were adapted from previous literature (e.g., [49]) and assessed on a seven-point Likert scale (1 = never; 7 = always).

2.1.5. Self-Control

Food waste has been found to result from competing motivations and goals [39]. A factor that has gained recognition in regard to reaching specific goals is self-control. Individuals who score higher on self-control tend to prioritize future goals over instant impulses [50]. To assess how self-control relates to food waste, we used the Brief Self-Control Scale [51].

2.2. Sample

From the end of 2018 to 2022, we recruited 165 households in a European country. Table 2 provides an overview of the demographics of the sample. To recruit the households, we used several communication channels (e.g., blogs, social media, mailing lists). The households were required to be in the loyalty program of one of the two major national retailers and willing to share their historical purchase data in digital form. The households received a financial incentive (~$20).

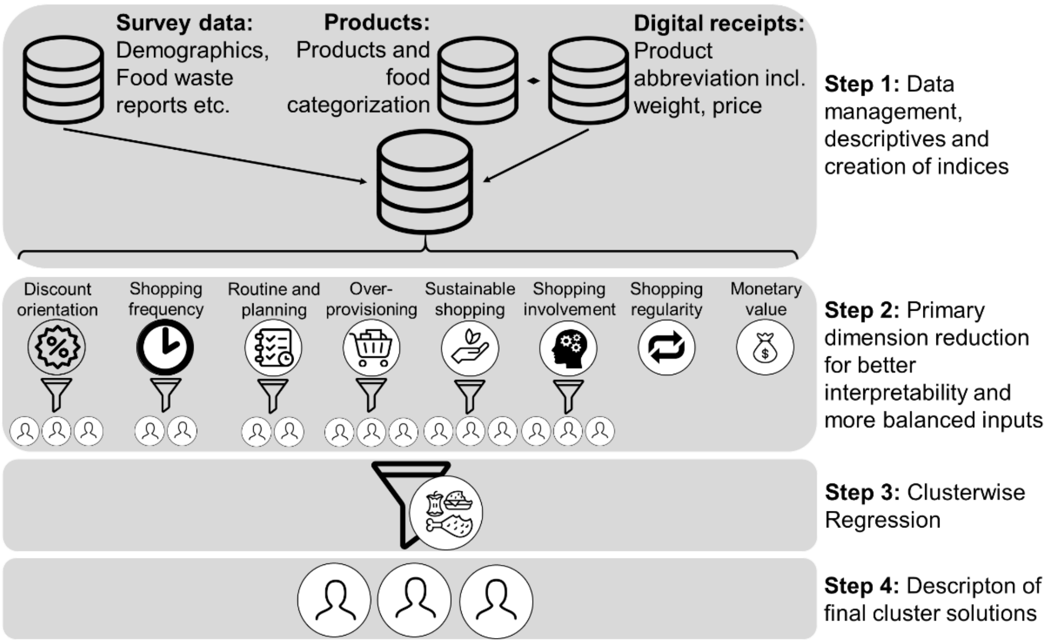

Figure 2. Visualization of the four-step analysis procedure.

2.3. Preregistration, Data, and Code Availability

We pre-registered our research questions and analysis plan after the data collection (but before the data analysis) on 12 May 2022 at OSF (see Supplementary Materials, anonymized pre-registration link: https://osf.io/qasfx/?view_only=1ebca45375cb42fcb76d2fed1316edde, accessed on 1 August 2022). We provided our material and code on the OSF project repository (anonymized project link: https://osf.io/85qu7/?view_only=ac342698f82f468ea9e86c8612761e22, accessed on 1 August 2022. Due to the sensitivity of the data, we are not allowed to make the digital receipts publicly accessible. The product data can be requested for scientific purposes.

2.4. Ethics

We obtained ethical approval for both the data collection (Ethics Committee of a European University on 10 October 2019) and validation study (Ethics Committee of a European University on 26 May 2020). This research complies with General Data Protection Regulation requirements.

2.5. Analysis

As they were pre-registered, we analyzed our data in four steps: First, we were concerned with the data management, that is, computing the descriptive quantitative indices based on raw purchase data (e.g., share of money spent on fresh items, number of date-related discounts; for an overview, see Section 3 in our pre-registration), deriving a mean score for the self-control scale and transforming our variables (z transformation).

Second, we conducted a preliminary dimension reduction. Due to the richness and variety of our raw data, we used a k-means clustering approach with the elbow method to derive consumer-oriented, meaningful, and interpretable subdimensions for six of our eight food waste predictors. Further, this ensures more balanced input variables for step three. We computed descriptive statistics for the resulting clusters.

Table 2. Overview of sample demographics (N = 165, see step 1 in Figure 2).

Demographic Variable	Frequency	Percentage
Gender		
Male	118	72%
Female	47	28%
Age		
18–29	64	38.8%
30–39	47	28.5%
40–49	30	18.2%
50–59	21	12.7%
60–69	3	1.8%
Household Size		
1	38	23.0%
2	56	33.9%
3	33	20.0%
4	25	15.2%
5	7	4.2%
6	4	2.4%
11	2	1.2%
Number of Kids		
0	112	67.9%
1	27	16.4%
2	19	11.5%
3	6	3.6%
4	1	0.6%
Annual Income		
<~$60,000 (1)	22	13.3%
~$60,001–~$88,000 (2)	21	12.7%
~$88,001–~$120,000 (3)	25	15.2 %
~$120,001–~$165,000 (4)	22	13.3%
>~$165,001 (5)	25	15.2%
No answer	50	30.3%
Education		
Basic education	10	6.1%
Intermediate education	28	17.0%
Advanced education	90	54.5%
No answer	37	22.4%

Third, for the main analysis, we computed a cluster-wise regression by fitting a finite mixture model (flexmix R-package [52]). Specifically, we fitted a linear regression with multiple response variables, namely, a household's self-reported food waste for the captured food categories (e.g., self-reported food waste for fruits, bread, and meat and fish). The respondent ID was our grouping variable. As predictors, we used the eight food waste drivers identified from previous research (see Table 1). The optimal number of clusters from our cluster-wise regression was determined by comparing the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the integration classification likelihood (ICL) of the different solutions.

Fourth, we computed diverse descriptive statistics for the clusters of the final cluster solution and analyzed which aspects were significantly different from each other (see Appendix B). The procedure or our analysis is summarized and visualized in Figure 2.

3. Results

3.1. Preliminary Clustering-Based Dimension Reduction

For six of the eight food waste drivers—*discount orientation* (1), *shopping frequency* (2), *planned shopping* (3), *overprovisioning* (4), *sustainable behavior* (5), and *shopping involvement* (6)—which we identified from previous research, we had a great deal of variables available. For efficient computation, and easy consumer-centered interpretability, we conducted a preliminary dimension reduction with a k-means approach (flexmix R-package, [37,38]). All input-variables were previously standardized. Table 3 provides an overview of the variables used for dimension reduction of the six food waste drivers. Dimensions 7 (shopping regularity) and 8 (monetary value) do not need a dimension reduction as they are one-dimensional already. Nevertheless, they were also standardized before proceeding.

For *discount orientation*, we found three segments: *non-discount shoppers*, characterized by a relatively low share of discounts and coupons used; *discount hunters*, characterized by a relatively high share of straight price discounts (compared to other clusters, *p-values* < 0.0001), multi-packages (compared to other clusters, *p-values* < 0.0001), and price-reduced multi-packages (compared to other clusters, *p-values* < 0.0001); and *discount optimizers*, characterized by significantly more expiry-date discounts (compared to other clusters, *p-values* < 0.0001) and food-specific and general coupons (compared to other clusters, *p-values* < 0.0001).

For *shopping frequency*, we found two clusters: *non-frequent* and *frequent shoppers*. The non-frequent shoppers had a significantly higher inter-purchase time in all categories (for all categories, *p-values* < 0.05).

For *planned shopping*, we found two clusters: *fill-up shoppers* and *big shoppers*. The fill-up shoppers had a lower inter-purchase time, bought fewer bags per trip, and had a lower variance in their basket size (all *p-values* < 0.001).

For *overprovisioning*, we found three clusters: stay-home, eat-out, and kids-provider shoppers. The stay-home shoppers had fewer kids than the kids-provider shoppers and ate out less often than the eat-out shoppers (all *p-values* < 0.001). Further, the eat-out shoppers had fewer kids and ate out more often than the kids-provider shoppers (all *p-values* < 0.001).

For *sustainable behavior*, we found three clusters: *non-sustainable shoppers*, characterized by a relatively low share of organic purchases (compared to the organic shoppers; *p-value* < 0.001), *social pseudo-sustainable shoppers*, who bought significantly more fairtrade products (all *p-values* < 0.001) and products with pseudo-sustainability labels (all *p-values* < 0.001), and organic shoppers, who bought a higher share of organic products (all *p-values* $\leq$ 0.001).

Finally, for *shopping involvement*, we found three clusters: uninvolved shoppers, producer-label shoppers, and private-label shoppers. The private-label shoppers had a higher share of private-label products (*p-values* < 0.0001), and the producer-label shoppers had a higher share of producer-label products than the other two clusters (*p-values* < 0.0001).

It is noteworthy that we added the results of the preliminary cluster-based dimension reduction to the data set, which we used for the cluster-wise regression. Specifically, we added a vector indicating the households' cluster assignment for the six food waste predictors (see Section 3.1 or Table 3 for a review) as well as the two additional predictors (i.e., shopping regularity and monetary value), which did not need a dimension reduction.

3.2. Identifying Food Waste Consumer Segments with a Cluster-Wise Regression Approach

To identify the food waste clusters, which we will use in our discussion on consumer-oriented interventions, we fitted a finite mixture model. Self-reported food waste from seven food categories was modeled as a response variable (repeated measures). As predictors, we used (1) *discount orientation*, (2) *shopping frequency*, (3) *planned shopping*, (4) *overprovisioning*, (5) *sustainable behavior*, (6) *shopping involvement*, (7) *shopping regularity*, and (8) *monetary value*. It is noteworthy that we used the cluster assignments identified in the preliminary dimension reduction for the first six predictors. More formally, we fitted the following model (expressed in flexmix notation, [52]):

Self-reported food waste ~ discount orientation + shopping frequency + planned shopping + overprovisioning + sustainable behavior + shopping involvement + shopping regularity + monetary value | respondent ID

Table 3. Overview of preliminary cluster-based dimension reduction (see step 2 in Figure 2).

Dimension	Segmentation Variables	Results and Cluster Description		
Discount orientation* *(1)	• Share of straight price discounts purchased • Share of multi-packages purchased without additional price discount • Share of further discounted multi-packages • Share of expiry-date discounts • Share of general coupons per trip • Share of food-specific coupons per trip	***No-discount shoppers*** Relatively young (compared to discount optimizers, *p-values* < 0.05) individuals who bought only few discounts	***Discount hunters*** Relatively young (compared to discount optimizers, *p-values* < 0.05) individuals who bought more regular discounts and multibuys (compared to others, *p-values* < 0.0001)	***Discount optimizers*** Older individuals (compared to other clusters, *p-values* < 0.05) who used coupons and bought expiry-date-related discounts (compared to others, *p-values* < 0.0001)
Shopping frequency* *(2)	Average inter-purchase time for fruits, veggies and salads, dairy products, meat and fish, bread, and sweets and snacks	***Non-frequent shoppers*** Shoppers who went to the store more infrequently (for all categories, *p-values* < 0.05) and had bigger households and better education (both *p-values* < 0.1)	***Frequent shoppers*** Shoppers who went to the store more frequently (for all categories, *p-values* < 0.05) and had smaller households and better education (both *p-values* < 0.1)	
Routine & planned shopping* *(3)	• Average number of grocery bags purchased per trip • Average inter-purchase time, not category-specific • Average basket size per trip and household member	***Fill-up shoppers*** Shoppers with lower self-control (*p-values* < 0.05), comparably constant basket sizes, who purchased fewer bags and went to the store more often (all *p-values* < 0.05)	***Big shoppers*** Shoppers with higher self-control (*p-values* < 0.05) and varying basket sizes, who bought more bags and went to the store less frequently (all *p-values* < 0.05)	
Overprovisioning* *(4)	• Energy (in kcal) purchased per household member and day, corrected by the share of retailer wallets • Number of kids living in a household • Share of meals from sources other than the retailer	***Stay-home shoppers*** Shoppers who ate at home more often than eat-out shoppers (*p-value* < 0.0001) and had fewer children than the kids-provider shoppers (*p-value* < 0.0001)	***Eat-out shoppers*** Shoppers who ate out frequently (compared to stay-home shoppers, *p-value* < 0.0001)	***Kids Provider shoppers*** Shoppers with more kids (compared to other clusters, *p-values* < 0.0001) and who lived in larger households (compared to other clusters, *p-values* < 0.05)
Sustainable shopping* *(5)	• Share of organic products purchased • Share of fairtrade products purchased • Share of regional products purchased • Share of sustainable products without a label (mostly plant-based meat and cheese substitutes)	***Non-sustainable shoppers*** Shoppers who bought a lower share of organic (compared to other clusters, *p-values* < 0.0001), social, and pseudo- (compared to social-pseudo-shoppers, *p-value* < 0.001) sustainable products	***Social Pseudo sustainable shoppers*** Shoppers who bought a higher share of products with social and pseudo-sustainability labels than other clusters (*p-values* < 0.001)	***Organic shoppers*** Shoppers who bought a higher share of organic products (compared to other clusters, *p-values* ≤ 0.0001) and are, compared to the non-sustainable shoppers, better educated (*p-value* < 0.05) and earn more (*p-value* < 0.1)
Shopping involvement (6)	• Share of weekend shopping trips, weighted by the basket size • Share of weekend shopping trip • Share of products with a private label • Share of products with a producer label	***Uninvolved shoppers*** Shoppers who did not score high on any dimension and therefore tend to be univolved [17]	***Producer-label shoppers*** Shoppers who bought a higher share of producer-label products (compared to other clusters, *p-values* < 0.0001)	***Private-label shoppers*** Shoppers who bought a higher share of private-label products (compared to other clusters, *p-values* < 0.0001)

Note. The dimensions reflect six of the eight food waste drivers for which we conducted the preliminary dimension reduction (see Table 1), which we entered in the cluster-wise regression model as predictors. The variables listed in the variables column reflect those entered in the k-means clustering, which we conducted to reduce the dimensionality of the six listed food waste drivers. In the *Results Cluster Description* column, we describe the clusters resulting from the preliminary dimension reduction step. The description of the resulting clusters can be found in Appendix A.

Based on the BIC and ICL heuristics, the K = 3 clusters appeared to be the best solution for these data, resulting in an aggregated R^2 of 0.35 (see Figure 3). Distinct food wasting patterns could be observed among the three clusters.

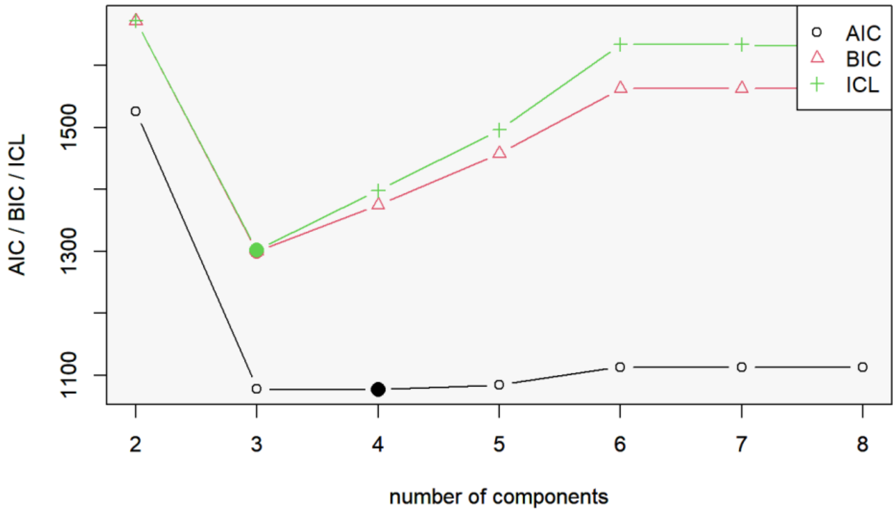

Figure 3. Overview of AIC, BIC, and ICL.

The *time-constrained* contained households that wasted food from time to time. The *convenience lovers* cluster included households reporting that they wasted relatively large amounts of food, whereas the *traditionals* contained households reporting that they wasted nearly no food (on average, 5% of the total weight of bought food). Apart from the categories of dairy products and meat and fish, where the *time-constrained* and *traditionals* did not differ in their self-reported food waste, the clusters were statistically different in all other categories (see Table 4).

Table 4. Description of traditionals, time-constrained, and convenience lovers (see step 4 in Figure 2).

Cluster Name	Segmentation Basis						
	Wasted Fruits	Wasted Veggies + Salad	Wasted Bread	Wasted Meals	Wasted Meat + Fish	Wasted Dary Products	Wasted Snacks + Sweets
Traditionals (n = 81)	0.05 (0.01) [b,c]	0.05 (0.00) [b,c]	0.05 (0.01) [b,c]	0.05 (0.01) [b,c]	0.05 (0.01) [b,c]	0.05 (0.01) [b,c]	0.05 (0.01) [b,c]
Time-constrained (n = 65)	0.11 (0.01) [a,c]	0.12 (0.00) [a,c]	0.11 (0.01) [a,c]	0.09 (0.01) [a,c]	0.06 (0.01) [a,c]	0.07 (0.01) [a,c]	0.07 (0.01) [a,c]
Convenience lovers (n = 19)	0.18 (0.01) [a,b]	0.16 (0.01) [a,b]	0.25 (0.01) [a,b]	0.19 (0.01) [a,b]	0.13 (0.01) [a,b]	0.17 (0.01) [a,b]	0.17 (0.01) [a,b]

Note. Table 4 shows the means (and standard deviations) of the corresponding variables. On a 5% significance level, [a] = significantly different from the traditionals; [b] = significantly different from the time-constrained; [c] = significantly different from the convenience lovers.

Table 5 presents the parameter estimates for each of the derived clusters resulting from the cluster-wise regression. For the *time-constrained*, eating out frequently seemed to drive cluster membership. At the same time, being more involved in the grocery shopping process, indicated by buying more producer-labeled products, decreased the probability of belonging to this medium-level wasting group. For the *convenience lovers*, we found that being a discount hunter increased the likelihood of belonging to this high-level wasting group.

Table 5. Parameter estimates for the finite mixture model.

Variables	Traditionals (49%)	Time−Constrained (39%)	Convenience Lovers (12%)
Intercept	0.36 (0.01) ***	0.07 (0.06)	1.43 (0.52) **
Discount orientation: discount hunter	0.00 (0.02)	−0.07 (0.08)	3.33 (1.64) *
Discount orientation: discount optimizer	0.00 (0.01)	−0.04 (0.09)	−0.31 (0.55)
Shopping frequency: non−frequent shopper	0.00 (0.01)	0.04 (007)	−0.46 (0.79)
Routine & planned shopping: big shopper	0.00 (0.01)	−0.12 (0.09)	−0.36 (0.94)
Overprovisioning: eat-out shopper	0.00 (0.01)	0.19 (0.06) **	−0.10 (0.56)
Overprovisioning: kids-provider shopper	0.00 (0.02)	−0.02 (0.07)	−0.56 (0.71)
Sustainable shopping: pseudo-sustainable shopper	0.00 (0.03)	0.03 (0.10)	−0.12 (0.54)
Sustainable shopping: organic shopper	0.00 (0.01)	−0.13 (0.11)	−0.16 (0.61)
Shopping involvement: private-label shopper	0.00 (0.01)	−0.12 (0.07)	1.24 (0.98)
Shopping involvement: producer-label shopper	0.00 (0.02)	−0.17 (0.08) *	0.06 (0.64)
Shopping regularity	0.00 (0.05)	−0.05 (0.05)	1.06 (1.02)
Monetary value	0.00 (0.05)	0.00 (0.05)	0.17 (0.29)

Note. *** $p \leq 0.001$, **: $p \leq 0.01$, *: $p \leq 0.05$, $p \leq 0.1$. The table shows means (and standard deviations) of the corresponding variables. Reference categories for the predictors: discount orientation = no-discount shoppers; shopping frequency = non-frequent shoppers; routine and planned shopping = fill-up shoppers; overprovisioning = stay-home shoppers; sustainable shopping = non-sustainable shoppers; shopping involvement = uninvolved shoppers.

The traditionals were significantly older than the others, had a high intention not to waste any food at all, and reported high involvement in planning and reusing leftovers. They followed a traditional diet without many plant-based substitutes. Compared to the traditionals, the time-constrained scored high on the share of products bought on weekends ($p < 0.05$), the share of products with producer-labels ($p < 0.05$) and the share of discounted multi-packages ($p < 0.05$). The convenience lovers were the youngest, had the lowest intention to produce no food waste at all, and therefore also reported the least number of activities in planning or reusing leftovers. They bought comparably more processed foods (perishability was significantly lower, $p < 0.05$) and plant-based substitutes (pseudo-sustainable products, $p < 0.05$). These results can be found in Table A1 in Appendix B.

To gain additional insights into how well the different groups reported their food waste, we also looked at our data from the validation study. To do so, we divided our sample into three equal parts. We found that, on average, the high wasters (*convenience lovers*) overreported (0.038, significantly different from the other groups), while the low-wasting group (*traditionals*; 0.041) and medium-wasting group (*time-constrained*; 0.024) underreported ($p < 0.05$).

4. Discussion

The overarching goal of this research was to explore the potential of retailers to reduce consumer food waste by implementing targeted interventions. We used a unique data set consisting of digital grocery receipts from a major retailer in a small European country and validated self-reported food waste measures to identify distinct groups of consumer food wasters. Computing a cluster-wise regression—with reported food wasting behavior as the dependent variable and actual purchase behavior as predictors—revealed three distinct groups: *traditionals*, *time-constrained*, and *convenience lovers*. While the traditionals tended to waste very little to no food, the time-constrained tended to waste some food from time to time. The convenience lovers were most prone to wasting large quantities of food. The distinct characteristics of the different food wasters provided a suitable basis to derive consumer-specific interventions.

4.1. Theoretical Implications

Our cluster results have similarities with existing taxonomies of food wasters. For example, Aschemann-Witzel et al. (2021) [22], Delley and Bunner (2017) [53], and Gaiani et al. (2018) [54] found a group of older frugal households that did not waste much food. In this study, the traditionals were also comparably old and engaged relatively frequently in food waste prevention. Further, multiple studies have identified a household cluster that is comparably young and care relatively little about the issue of food waste [22,53,55]. This pattern was similar for our convenience lovers. Finally, other researchers have found a

"Young Foodies" cluster, that is, relatively young consumers who are involved with food, find food waste important, but still waste food. Our last group, the time-constrained, was similar to this group of young foodies [22].

To assess the accuracy of the different groups' food waste reporting, we used the sample from the validation study (see Section 2.1.2) to create groups with similar food wasting behavior. Based on these results, we find that the low-wasting group tends to underreport. Therefore, the traditionals' low food waste could be (partly) driven by their tendency to underreport. While food waste research has repeatedly highlighted the significance of diverse (cognitive) biases leading people to underreport their food waste [40], we currently lack clarity regarding the psychological determinants, mechanisms, and approaches regarding how to correct these biases (either in a preventive manner or retrospectively in a statistical manner).

Our results also reveal that the consumers in the three clusters showed stable food waste patterns across different food categories (e.g., fruits, meat), implying that food waste was a rather stable behavioral pattern in relation to certain food categories. Previous research supports the independence of food waste within this food category (e.g., fruits, meals) [56], pointing to the importance of promoting skills and knowledge that apply to a wide range of food categories (vs. isolated food categories).

Furthermore, we found that three factors significantly predicted cluster membership. First, we found that eating out frequently predicted whether someone belonged to the time-constrained. According to Evans et al. [39], eating out was frequently closely connected to not eating leftovers, a conclusion supported by our data, which showed that the time-constrained had a lower degree of self-reported reuse of leftovers. As Evans et al. [39] explained, this could be due to consumers' working duties and social life.

Second, we found that high shopping involvement, as indicated by a high share of producer-labeled products, decreased the probability of belonging to the time-constrained. Interestingly, this potentially implies that increasing shopper involvement can reduce food waste. However, future research is needed to test this.

Third, our analysis shows that being a discount hunter (buying a high share of straight price discounts, multi-packages, and discounted multi-packages) increased the likelihood of being a convenience lover. Importantly, existing research does not provide a clear picture of the impact of price discounts on food waste [27]. Our results are in line with this inconclusive evidence as we found that the relationship between price discounts and food waste might vary depending on diverse consumer characteristics. For example, we found that the discount hunters were, on average, younger than the discount optimizers (7.21 years, $p = 0.027$). Younger individuals were previously found to be associated with a higher proneness to deals [57], which was associated with overprovisioning [18].

Overall, our findings are broadly in line with existing evidence. Most importantly, our research suggests digital receipts should be used to predict food waste, for example, because it is cost-efficient and can overcome certain disadvantages of survey-based food waste measures [25]. Finally, we strengthen evidence demonstrating the importance of distinguishing between different types of consumers and identifying factors that are relevant for effective interventions.

4.2. Practical Implications

Researchers have explored diverse consumer food waste interventions such as normative messages, feedback, and awareness campaigns [58,59]. To date, however, food waste research has widely neglected the importance of more individualized behavior change approaches where different consumer groups are targeted with tailored interventions, moving away from a standardized one-size-fits-all approach [21]. In fact, interventions are more effective when they are designed to match people's actual psychology, that is, their motives, attitudes, habits, and behavior. This often implies the consideration that consumers are at different stages of the behavioral change process.

Consumers who are not yet aware of the negative consequences of food waste for the environment and society typically need alternative interventions than those intended for consumers who are already concerned with food waste, enact personal norms to use their leftovers, and do not throw away food due to expiry dates [21,60]. Consumers who are not yet aware of the negative consequences of food waste, for instance, can often be effectively targeted by awareness campaigns, including those providing normative or monetary information or topic-related pictures that elicit emotions. Consumers who are already concerned about food waste and advanced in their behavioral change process might benefit more from tools and prompts that make desirable behavior easy to follow or help them manage time-constrained or other competing motivations. An example could be an app to plan shopping trips or send notifications about expiry dates of food stored in the refrigerator.

Transferring this insight to the present consumer food waste typology, it follows that interventions need to be tailored to the consumers in the three clusters. In fact, the three clusters differ in terms of habits and behaviors such as whether they frequently buy discounts or eat out. Having said this, the deal-prone *convenience lovers* could be targeted by retailers with an intervention that aims to reduce their deal proneness, such as by showing food waste-corrected prices (e.g., making it salient that they pay more per kg if they waste parts of it) or making the cost savings of not wasting food more salient (e.g., "buy two instead of three as one will be wasted anyways"). Although this group seems to be the one that is the least concerned with food waste, it is the one that buys the biggest share of sustainable convenience food. This implies that focusing on framing food waste as a sustainability issue might be a promising behavior change approach for retailers. On a general level, this group is potentially in a phase of a behavioral change process where either behavioral intentions or implementation intentions must be formed. To do so, interventions should be targeted at forming attitudes towards reducing food waste, increasing perceived behavioral control, or by helping them to actually implement their intentions. Figure 4 provides an overview about potential interventions [21,61].

For the *traditionals*, our results suggest that, given their tendency to underreport food waste, it might be interesting to use a feedback-based intervention that targets misperceptions of how much food they waste. Filling in a food waste diary or using a bin that records and provides information about food waste could help inform them about their misperceptions and real food waste amounts and, thus, motivate them to reduce food waste (see, e.g., [62]). Further, given that this group is already quite involved in food waste reduction, tools that help them to habitualize the corresponding behaviors should be used [61]. Figure 5 shows ideas for potential interventions.

Figure 4. Profile of convenience lovers and potential interventions.

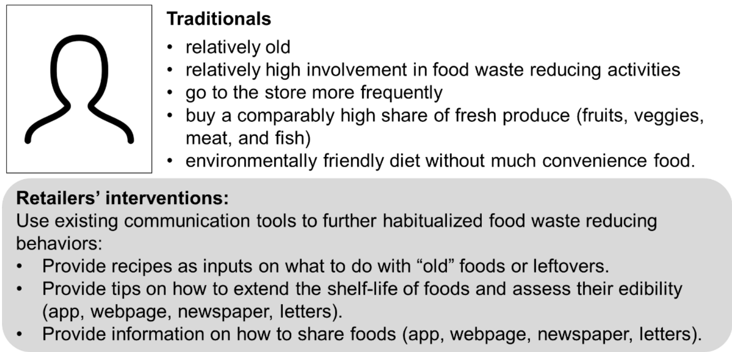

Figure 5. Profile of traditionals and potential interventions.

For the *time-constrained*, our findings suggest that making desirable behaviors suitable for their irregular everyday life is key. In fact, the *time-constrained* seemed to waste food due to occasions such as eating out. Here, apps that support planning or provide tips on how to deal with leftovers (e.g., freezing, sharing) could be helpful. Providing these individuals with tools on how to deal with competing goals is also relevant in regards to habitualizing food waste-reducing behaviors [21,61,63]. Figure 6 shows ideas on how this can be achieved.

Another important aspect regarding discriminating among the different consumer food waste clusters is that we can consider which cluster might benefit most from targeting. For instance, it might be a priority to target a cluster that is likely to shift significantly toward more sustainable consumer practices than address a cluster that is already close to having internalized food waste avoidance behaviors as habitual.

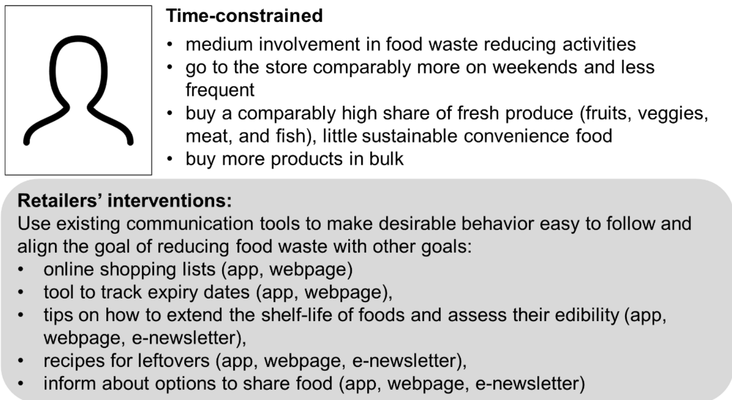

Figure 6. Profile of time-constrained and potential interventions.

A slightly different approach could be to target segments based on different communication channels. Young and colleagues [16] showed that a social media-based intervention targeting leftover-reducing behaviors via social influence did not outperform standard information-based interventions in newspapers (tips for storage, recipes, and advice on how to use leftovers) and e-newsletters (tips on the reuse of leftovers and storage). We argue that this could be the result of varying communication preferences of different consumer types. Consumers such as the traditionals might prefer newspapers and hence be particularly susceptible to interventions delivered via newspapers. Other consumer types such as the time-constrained or convenience-lovers might rather rely on online communication and hence be more susceptible to a short and easy-to-understand video with tips on how to avoid food waste (e.g., leftover receipts, tips for storage). Overall, this underscores that there is a great benefit in customizing the content and communication of food waste interventions. Future research could systematically examine the role of personalized intervention and experiment with testing different communication channels.

4.3. Limitations and Future Research

Although our dependent variables were self-reports, there was evidence of their validity from our compositional analysis. However, the analysis of the data from the validation revealed that our measures were still subject to bias. For example, respondents might not remember exactly how much they wasted or feel bad about their actions and, therefore, not report true values. Furthermore, reporting a percentage of how many groceries were wasted is an error-prone, cognitively-demanding task [40].

While we did find some relations between shopping and wasting behavior, our sample was small. This is likely rooted in the very extensive process of gathering and sharing the data. Further research should investigate replicating such findings based on larger samples. Since we used only a fraction of the variables that could be extracted from the digital receipts, other predictors should also be considered. Independent of our small sample, our findings provide evidence of the potential of grocery basket data in detecting possible drivers of food waste.

From a behavioral change perspective, it would be interesting for future research to consider integrative behavioral change frameworks (e.g., stage models of behavioral change), when setting up surveys. Integrative behavioral change frameworks aim to capture various psychological constructs important to behavioral change (e.g., emotions, social norms, self- and collective-efficacy, attitudes). Consumer groups that differ in the extent to which they score on these psychological constructs require different interventions for effective behavioral change. For example, consumers that think that it is widely accepted that households waste food or consumers that do not think that there is collective effort to tackle food waste among the population, could be targeted by normative interventions. In contrast, households that report that there is the norm that households do not waste food and that there is collective effort to do something against food waste may profit more from an intervention that addresses the fostering of a couple of specific habits (e.g., storage procedures) [64]. Given the frequent interaction between retailers and customers, it is a promising solution to collect these variables through the retailer. Generally, this additional knowledge could result in further possibilities for retailers to intervene. For example, they could adapt the order of products in the online store or add group-specific tags on certain products or package sizes.

Lastly, we highlight one potential pathway of action for retailers. It is however not sufficient to fully rely on helping consumers reduce food waste. Given their power over the whole supply chain, retailers can leverage their position to overcome systemic issues and boost food waste prevention [65,66]. Future research should further investigate the retailers' role and how they can help to mitigate food waste along the whole food supply chain. Finally, we encourage researchers to collaborate with retailers and test individualized interventions in the field.

5. Conclusions

In this research, we used real-world loyalty-card shopping data and food waste self-reports to identify consumer food waste groups that could provide information to retailers about the design of targeted interventions aimed at fostering more sustainable consumer practices. We identified three consumer food waste groups—traditionals, time-constrained, and convenience lovers. This research provides a base for the implementation of evidence-based targeted interventions that effectively tackle consumer food waste.

Supplementary Materials: The following supporting information can be downloaded at: https://osf.io/qasfx/?view_only=1ebca45375cb42fcb76d2fed1316edde (accessed on 1 August 2022): anonymized pre-registration link; https://osf.io/85qu7/?view_only=ac342698f82f468ea9e86c8612761e22 (accessed on 1 August 2022): material and code.

Author Contributions: Conceptualization: S.M., S.S. and M.N.; methodology: S.M. and S.S.; validation: S.M., S.S. and M.N.; formal analysis: S.M. and S.S.; investigation: S.M. and S.S.; data curation: S.M. and K.L.F.; writing (original draft preparation): S.M. and S.S.; writing (review and editing): K.L.F.

and M.N.; visualization: S.M. and S.S.; supervision: M.N.; project administration: S.M.; funding acquisition: S.M., K.L.F. and M.N. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (or Ethics Committee) of ETH Zurich (main study, EK 2019-N-134, date of approval: 3 September 2019) and the University of Zurich (validation study, OEC IRB #2020-028, 26 May 2020). The research complies with General Data Protection Regulation requirements.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data sharing of the digital receipts is not applicable due to the fact that the data contain information that potentially makes participants identifiable. The product data base is expected to be published soon and will be made available for scientific purposes upon request.

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Appendix A

Table A1. Descriptors of clusters from the preparatory cluster analysis.

Segmentation Basis/Cluster Name	Age	Gender (% m)	BMI	Self-Control	Education	Income	Household Size	Number of Kids
Non-discount shopper	34.3 (1.14) [c]	0.69	23.9 (0.42)	30.2 (1.92)	2.59 (0.07)	3.27 (0.15)	2.42 (0.16)	0.46 (0.09)
Discount hunter	32.5 (2.16) [a]	0.78	25.7 (0.80)	30.8 (3.62)	2.70 (0.13)	3.79 (0.27)	2.74 (0.30)	0.74 (0.17)
Discount optimizer	39.7 (1.73) [a,b]	0.74	25.1 (0.64)	27.0 (2.90)	2.67 (0.12)	3.27 (0.22)	2.95 (0.24)	0.55 (0.14)
Non-frequent shopper	35.6 (1.06)	0.74	24.5 (0.39)	28.8 (1.73)	2.70 (0.07)	3.37 (0.13)	2.77 (0.14) [b]	0.61 (0.08)
Frequent shopper	34.8 (1.66)	0.65	24.5 (0.60)	31.2 (2.71)	2.48 (0.10)	3.34 (0.21)	2.21 (0.22) [a]	0.33 (1.13)
Fill-up shopper	35.6 (0.99)	0.72	24.7 (0.36)	27.4 (1.58) [b]	2.62 (0.06)	3.36 (0.12)	2.61 (0.13)	0.49 (0.08)
Big shopper	34.3 (2.06)	0.68	23.8 (0.75)	38.3 (3.29) [a]	2.65 (0.11)	3.35 (0.27)	2.58 (0.28)	0.71 (0.16)
Stay-home shopper	35.5 (1.39)	0.74	24.2 (0.50)	32.3 (2.24)	2.50 (0.08)	3.11 (0.17)	2.49 (0.18)[c]	0.16 (0.05) [c]
Eat-out shopper	34.9 (1.38)	0.73	24.5 (0.50)	26.2 (2.23)	2.76 (0.09)	3.51 (0.17)	2.39 (0.18) [c]	0.23 (0.05) [c]
Kids-provider Shopper	36.3 (2.26)	0.62	25.3 (0.82)	30.7 (3.66)	2.65 (0.14)	3.58 (0.28)	3.50 (0.30) [a,b]	2.31 (0.09) [a,b]
Non-sustainable shopper	36.3 (1.03)	0.70	24.8 (0.50)	27.8 (1.68)	2.55 (0.06) [c]	3.50 (0.13)	2.53 (0.14)	0.54 (0.07)
Pseudo-sustainable shopper	30.6 (3.04)	0.86	24.4 (0.50)	34.1 (4.98)	2.62 (0.17)	3.03 (0.38)	2.43 (0.41)	0.29 (0.24)
Organic shopper	33.8 (2.15)	0.71	23.2 (0.82)	34.8 (3.52)	2.91 (0.13) [a]	2.88 (0.27)	2.54 (0.29)	0.61 (0.17)
Producer-label shopper	35.4 (1.14)	0.68	24.7 (0.41)	29.5 (1.84)	2.73 (0.07)	3.34 (0.14)	2.47 (0.15)	0.47 (0.08)
Private-label shopper	35.4 (2.46)	0.82	24.7 (0.89)	22.5 (3.96)	2.38 (0.16)	3.55 (0.31)	2.64 (0.33)	0.36 (0.19)
Uninvolved shopper	35.3 (1.80)	0.76	23.8 (0.65)	33.1 (2.90)	2.51 (0.11)	3.30 (0.22)	2.93 (0.24)	0.76 (0.14)

Note. The table shows the means (and standard deviations) of the corresponding variables. On a 5% significance level, [a] = significantly different from the first cluster mentioned; [b] = significantly different from the second cluster mentioned; [c] = significantly different from the third cluster mentioned.

Appendix B

Table A1. Extended descriptors.

Cluster Name/Segmentation Basis	Traditionals (49%)	Time-Constrained (39%)	Convenience Lovers (12%)
Gender (share of men)	0.675	0.76	0.71
Age	32.3 (0.989) ^{b}	39.2 (0.89) ^{a,c}	26.3 (1.81) ^{b}
BMI	24.1 (0.38)	24.5 (0.34)	24.2 (0.70)
Education	2.62 (0.06)	2.62 (0.06)	2.6 (0.12)
Number of kids	0.46 (0.08)	0.60 (0.07)	0.38 (0.14)
Household size	2.74 (0.14)	2.41 (0.13)	2.76 (0.27)
Education	2.62 (0.06)	2.62 (0.06)	2.60 (0.12)
Income	3.55 (0.14)	3.17 (0.13)	3.51 (0.26)
Intention to waste no food at all	6.57 (0.05) ^{b,c}	6.80 (0.05) ^{a,c}	6.15 (0.11) ^{a,b}
Intention to eat all purchased food	6.70 (0.07) ^{c}	6.55 (0.07) ^{c}	5.79 (0.14) ^{a,b}
Intention to waste only little food	6.77 (0.06) ^{c}	6.60 (0.06) ^{c}	6.21 (0.12) ^{a,b}
Intention to reuse leftovers	6.74 (0.07) ^{c}	6.48 (0.07) ^{c}	5.50 (0.15) ^{a,b}
Systematic storing	4.69 (0.18)	4.18 (0.20)	3.86 (0.38)
Overpreparing food	3.26 (0.15) ^{c}	3.67 (0.17)	4.29 (0.32) ^{a}
Redistributing food Assessing the edibility	3.00 (0.18) ^{b,c} 5.80 (0.06)	3.64 (0.20) ^{a,c} 6.17 (0.12)	4.86 (0.37) ^{a,b} 5.86 (0.24)
Planning	5.09 (0.14) ^{c}	5.72 (0.13) ^{a,c}	4.43 (0.27) ^{a}
Storing	4.69 (0.18)	4.18 (0.20)	3.86 (0.38)
Reuse of leftovers	6.04 (0.01) ^{b,c}	6.50 (0.09) ^{a,c}	5.29 (0.18) ^{a,b}
Vegetarian diet	0.08	0.11	0.20
Environmentally friendly diet	0.29 ^{b}	0.14 ^{a}	0.12
Healthy (= no disease)	0.76	0.83	0.91
Share of savings	0.07 (0.01) ^{b,c}	0.06 (0.01) ^{a}	0.04 (0.01) ^{a}
Share of private labels	0.28 (0.01)	0.25 (0.01)	0.31 (0.02)
Share of producer labels	0.09 (0.01) ^{b}	0.11 (0.01) ^{a}	0.10 (0.01)
Share of fruits and vegetables	0.27 (0.01)	0.30 (0.01) ^{c}	0.23 (0.02) ^{b}
Share of meat and fish	0.35 (0.01) ^{c}	0.37 (0.01) ^{c}	0.30 (0.02) ^{a,b}
Share of bread	0.29 (0.01) ^{c}	0.30 (0.01) ^{c}	0.23 (0.02) ^{a,b}
Perishability of basket (1–3)	1.42 (0.02) ^{c}	1.41 (0.02) ^{c}	1.54 (0.03) ^{a,b}
Share of meat and fish	0.35 (0.01)	0.37 (0.01) ^{c}	0.30 (0.02) ^{b}
Share of bread	0.29 (0.01) ^{c}	0.30 (0.01) ^{c}	0.23 (0.02) ^{a,b}
Share of multi-packages	0.01 (0.00)	0.02 (0.00)	0.01 (0.00)
Share of straight price discounts	0.03 (0.00)	0.03 (0.00)	0.02 (0.01)
Share of discounted multi-packages	0.00 (0.00) ^{b}	0.01 (0.00) ^{a}	0.00 (0.00)
Share expiry date-related discounts	0.02 (0.00)	0.02 (0.00)	0.02 (0.00)
Share of value spent per person	1683 (172)	1206 (192)	1073 (351)
Ave. inter-purchase time (in days)	8.54 (0.69) ^{b}	6.09 (0.77) ^{a}	5.97 (1.4)
Standard deviation of inter-purchase time	9.65 (1.02)	7.27 (1.14)	6.32 (2.08)
Share of products bought at weekends	0.22 (0.01) ^{b}	0.30 (0.02) ^{a}	0.24 (0.03)
Share of pseudo-sustainable products	0.00 (0.00) ^{c}	0.01 (0.00) ^{c}	0.01 (0.00) ^{a,b}
Share organic products	0.18 (0.01)	0.16 (0.02)	0.17 (0.03)
Share social (fairtrade) products	0.02 (0.00)	0.02 (0.00)	0.02 (0.00)

Note. The table shows means (and standard deviations) of the corresponding variables. On a 5% significance level, ^{a} = significantly different from the traditional; ^{b} = significantly different from the time-constrained; ^{c} = significantly different from the convenience lovers.

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