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An analysis of household food waste determinants in Brazilian metropolitan areas

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ABSTRACT

Data from the UN's Food and Agriculture Organization reveal that about one-third of global food intended for human consumption is wasted annually. This study investigated the determinants of household food waste in Brazilian metropolitan areas using an online survey. An ordered logit model was employed due to the hierarchical nature of the dependent variable. The results indicated that higher income and education levels correlate with increased waste; however, affluent households exhibited an inverse relationship. Effective nutrition planning reduced waste, while certain kitchen tools, training, and socio-environmental awareness also contributed to waste reduction.

Keywords: *Food waste; food security; household behaviour; ordered logit model.*

1 Introduction

In 2020, nearly 10% of the global population experienced undernourishment (WHO, 2021). Paradoxically, the Food and Agriculture Organization of the United Nations (FAO) reported that one-third of the global food produced for human consumption is either lost or wasted (FAO, 2011). Food loss (FL) pertains to inefficiencies throughout the food supply chain up to, but not including, the final consumer. Conversely, food waste (FW) specifically transpires at the consumer stage. Such loss and wastage not only intensify food insecurity but also signify a suboptimal utilization of resources (FAO, 2019). The United Nations Environment Programme (UNEP) estimates an annual FW of 931 million tons from households, retail sectors, and food services, with households contributing to 61% of this wastage (UNEP, 2021). Understanding the underlying causes of FW at the household level is pivotal for devising strategies to enhance food management during consumption.

Brazil, a major global agricultural player, saw its agribusiness exports ascend to US$ 120.5 billion in 2021, marking a 20% increase from 2020 (AGROSTAT, 2018). However, despite this economic achievement, Brazil confronts significant domestic challenges. A 2022 survey indicated that amidst the Covid-19 pandemic, approximately 125 million Brazilians faced food insecurity, with 33 million experiencing acute hunger (PENSSAN, 2022). Broken down, 31% of the population faced severe to moderate food insecurity, 28% encountered mild insecurity, and a mere 41% were food secure. Globally recognized factors such as geopolitical conflicts, environmental anomalies, economic downturns, and rising inequality contribute substantially to these food security challenges (FAO *et al.*, 2022). Within Brazil, daily food waste is estimated at 39,000 tons, making it one of the top ten food-wasting nations (Martins *et al.*, 2022). On a more granular level, Brazilian households dispose of around 353 grams of food daily, or 128.8 kg yearly, leading to a per capita wastage of 114 grams daily and 41.6 kg annually (Porpino *et al.*, 2018).

In the research conducted by van Geffen *et al.* (2016), various factors, including individual characteristics, societal norms, household infrastructure, and specific skill sets, have been identified as pivotal determinants of food waste (FW) at the consumer level. Typically, empirical research delves into a set of explanatory variables, encapsulating age, familial income, level of education, professional occupation, marital status, strategies for food shopping, culinary routines, food preservation techniques, leftover management, and the structural setup of kitchens. A profound comprehension of these elements' interplay is paramount when devising strategies to mitigate FW (Li *et al.,* 2022).

However, a recurrent challenge in FW research is the intricate process of accurately cataloging both the kind and volume of waste within domestic and food service settings. To navigate this, scholars have employed an array of assessment tools. These range from tangible measurements, such as physically weighing discarded items and monitoring garbage disposal, to more abstract methodologies like interviews and questionnaire-based surveys (Xue *et al.,* 2017). Each approach offers a unique blend of benefits and setbacks, often weighed in terms of time consumption, financial considerations, precision, impartiality, and dependability. In studies encompassing vast sample sizes, while direct measurements offer meticulous detail and accuracy, their applicability is often undermined by practical constraints. For instance, accurately gauging FW demands the use of calibrated scales and dedicated training, making it cumbersome for individuals to document discarded food consistently. On the other hand, surveys constitute a viable alternative to expansive, budget-conscious studies, although they rely heavily on the individual's accuracy in observing and documenting the nuances of food waste (van Herpen *et al.,* 2019).

The primary purpose of this research was to elucidate the factors influencing food waste (FW) behavior among residents of specific metropolitan areas in Brazil. Utilizing a sample of 511 valid responses, the study gathered data on household FW practices. A designed survey prompted respondents to detail the frequency, volume, and variety of food they discarded at their homes. Moreover, the questionnaire procured data regarding respondents' demographic details, household food handling practices, and their awareness about FW. For a nuanced understanding of the intensity and magnitude of domestic FW, participants' feedback was categorized using a Likert-type scale. Given the ordinal nature of the variables in question, an ordered logit model, as suggested by Greene (2002), was deemed the most suitable empirical approach for this analysis.

2 Some Empirical Evidences

Empirical research has consistently shown that food waste (FW) emanates from a myriad of management-associated behaviors at various stages: planning, procurement, storage, and utilization of food within households and food services. At each juncture in the food acquisition and preparation process, individual determinants such as cultural background, demographic attributes, lifestyle choices, and perceptions significantly impact FW (Heng and House, 2022). A profound understanding of the determinants influencing FW across its various forms is crucial for the design and execution of effective policies targeting its reduction or prevention at the consumer level. In pursuit of this objective, a plethora of studies employing diverse methodological tactics have sought to unravel the intricacies of consumer behavior vis-à-vis FW (Fanelli, 2019). Web-based questionnaires serve as pivotal tools, facilitating the quantification of the volume, variety, and regularity of domestic food disposal based on qualitative data (Jörissen *et al.*, 2015). Furthermore, responses garnered from interviewees to qualitative inquiries can encapsulate varying levels of concurrence, intensity, or regularity, typically captured via Likert-scale codifications (Qi and Roe, 2016).

In a comprehensive international survey spanning the US, Canada, the UK, and France, Heng and House (2022) sought to quantify household behaviors regarding the disposal of fresh fruits and vegetables that had become inedible. Respondents were prompted to indicate the frequency with which they discarded such produce. The ordinal frequency scale for responses encompassed: Ever (1), Rarely (2), Sometimes (3), and Often (4). Employing an ordered probit model, the research estimated the likelihood of an underlying variable indicating the extent of food waste (FW) for each individual, contingent on a set of demographic attributes provided by the respondents. It's worth noting that analogous models utilize the ordered logit method to gauge the probability of FW based on a collection of determinative variables, as demonstrated in studies by Qi and Roe (2016) and Hazuchova *et al.* (2020).

The existing literature consistently identifies certain commonalities in the determinants of food waste (FW) decisions. Predominantly, studies underscore the significance of family composition and demographic attributes as key influencers of FW behaviors. Specifically, the volume, frequency, and nature of food discarded are postulated to hinge on variables such as family size, educational attainment, income bracket, age distribution, gender dynamics, marital status, and employment circumstances (Annunziata *et al.,* 2022; Li *et al.,* 2022). In a localized assessment of Shenzhen, Zhang *et al.* (2018), alongside Edjabou *et al.* (2016)'s scrutiny of Danish households, discerned that FW volumes escalate in tandem with the growth of family size. Intriguingly, several studies suggest that on a per capita basis, FW diminishes as the household size expands. However, for a precise estimation of per capita waste volumes, it's imperative to employ direct quantification methodologies of FW, as highlighted by Schanes *et al.* (2018) and Jörissen *et al.* (2015).

Van Geffen *et al.* (2016) suggest that an elevated level of education corresponds with an increase in FW. This assertion, however, does not find unanimous agreement in academic circles. Schanes *et al.* (2018) posit that individuals with a higher education are more amenable to messages from food-saving campaigns, potentially leading them to waste food less frequently. On the subject of household income, a majority of research underscores a direct correlation between increased income and FW (cited by Zhang *et al.,* 2018; Secondi *et al.,* 2015). Yet, Setti *et al.* (2016) argue that those in higher income brackets tend to purchase more value-added products, resulting in diminished waste. Consequently, the association between income and FW can be visualized as an inverse U-shaped curve; FW intensifies with rising income but starts to taper off among the more affluent segments of society.

While international literature lacks a consensus on how age impacts food waste (FW) (Schanes *et al.,* 2018), the majority of studies explored in this research suggest that as individuals age, they tend to waste more food (Secondi *et al.,* 2015; Karunasena *et al.,* 2021). The effect of gender on FW remains unclear, with Schanes *et al.* (2018) noting its ambiguous influence. Visschers *et al.* (2016) observed that women waste more food than men, yet Cecere *et al.* (2013) found the opposite. Both Bretter *et al.* (2022) and Principato *et al.* (2015) reported no significant gender differences in this regard. As for marital status, the findings are mixed. Abd Razak (2017) suggested that single consumers are more adaptable in reducing FW, while Sunday *et al.* (2022) concluded that those in married households tend to waste less food compared to single individuals.

Mallinson *et al.* (2016) describe occasional consumers as individuals who only occasionally plan their meals and often opt for ready-to-eat foods. These consumers tend to waste food more frequently. Household food waste (FW) is largely influenced by food management routines, like planning shopping trips and monitoring food inventory (Romani *et al.,* 2018; Stefan *et al.,* 2013). Families that shop more frequently to better align with daily needs tend to reduce FW. Also, there's evidence that suggests excessive purchasing can lead to increased FW, especially when frequent shopping trips are driven by discounts and sales. However, creating a shopping list can turn a sudden shopping spree into a more organized activity, helping to reduce waste (Mattar *et al.,* 2018). Another approach to planning food purchases involves paying attention to product labels. In a study conducted with American consumers online, Kavanaugh and Quinlan (2020) noted that those who accurately understood food labels reported wasting food less often.

Individual characteristics and effective food management procedures play a critical role in preventing household food waste (FW). The importance of technological interventions cannot be understated. For instance, the adoption of Smart Fridges, the use of electrolyzed water, and innovative packaging methods have been identified as essential in extending the shelf-life of products (Cappelletti *et al.* 2022). Moreover, practicing efficient food preparation techniques, enhancing skills in cooking with leftovers, and strategic freezing can contribute significantly to repurposing edible food (Schanes *et al.,* 2018; Carroll *et al.,* 2021; Karunasena *et al.,* 2021).

There's a consensus in the literature about the pivotal role of consumer awareness and attitudes in reducing FW. A noteworthy observation is that while American consumers often reject food with visual imperfections, this trend diminishes among those who have heightened environmental consciousness (Aschemann-Witzel *et al.,* 2015). Comber and Thieme (2012) illustrated how images of overflowing trash cans on social media platforms can invoke feelings of guilt among consumers, prompting them to reconsider their recycling and FW habits. Some researchers even propose that dining out can be seen as a strategy to mitigate FW at home (Talwar *et al.,* 2021). However, a recurrent theme in empirical studies is the intricate balance between food safety and FW. Watson and Meah (2013) have argued that while environmental considerations can act as a deterrent to FW, concerns about food safety might inadvertently escalate FW. This is largely because individuals generally prioritize avoiding health risks associated with food. Furthermore, as incomes rise and food choices diversify, households face increased challenges in managing their food, which can unintentionally elevate FW levels (Thyberg and Tonjes, 2016).

3 Theoretical Model

Becker's Theory of Allocation of Time posits that households gain utility from consuming product Z, based on a utility function individuals strive to optimize within their budget constraints. Rather than immediately consuming the goods they buy, households merge inputs x with time T_x, transforming them into Z goods following the production function $Z_i = f(x, T_x)$ (Becker, 1965). In Lusk and Ellison's adaptation of Becker's model, households turn raw food inputs (x) and time (t_f) into meals (z) using the production function $z = f(x, t_f)$. FW represents raw food inputs not converted into meals (Lusk and Ellison, 2016).

Landry and Smith (2017) discussed a perspective on production inefficiencies where unused food ingredients in household cooking are deemed wasteful. They broke down the household decision-making into two distinct phases: the production phase, referred to as the lower stage, and the consumption phase, termed the upper stage. Within the lower stage, it's assumed that home cooking uses various inputs, labeled as x_1 (such as raw food, cooking ingredients, energy for heating and freezing, labor, etc.) to create meals over a period represented by t_1. This is influenced by the technological parameter, φ. During this food preparation phase, there's a belief that there exists an ideal level of input use, symbolized as $\mathrm{x}_1^{\mathrm{o}}$ (with $\mathrm{x}_1^{\mathrm{o}} \leq \mathrm{x}_1$), which reduces the costs of home-cooked meal production. Any excess beyond this optimal input level, represented by $(\mathrm{x}_1 - \mathrm{x}_1^{\mathrm{o}})$, is viewed as food waste (FW).

The current model suggests that households aim to get the most satisfaction from consuming two types of nutritional products: homemade (z_1) and ready-made (z_2). To make homemade food, one uses ingredients bought from the market (x_1), dedicates a certain amount of time (t_1), and employs various tools, appliances, and knowledge, denoted as technology φ. This results in z_1 quantities of food, as defined by the production function G_1.

$$z_1 = G_1\,(x_1, t_1; \varphi)$$

As a result, the indirect utility function for household food production z_1 can be depicted as:

$$U_{z_1} = U\,[G_1\,(x_1, t_1; \varphi)]$$

Families also purchase ready-made food (x_2), which, after some preparation (heating, freezing, washing, cleaning, storing, etc.), becomes available for consumption as z_2. The production of z_2 requires time t_2 and employs technology φ[1], as defined by the production function G_2.[2]

$$z_2 = G_2\,(x_2, t_2; \varphi)$$

Accordingly, the household indirect utility function for ready-made meals z_2 is:

$$U_{z_2} = U\,[G_2\,(x_2, t_2; \varphi)]$$

The total amount of food served by the household is $z = (z_1 + z_2)$. Therefore, the individual household utility function from food consumption is represented as:

$$U_{z_e} = U[(z_1, z_2);\ \tau],$$

Where τ represents a taste parameter that influences the translation of leisure and purchased goods into consumer utility (Huffman, 2010).

In the household production stage, we assume, following Landry and Smith (2017), that the difference between the food input used (x_1) and its cost-minimizing level (x_1^o) represents FW, such that.

$$w_1 = (x_1 - x_1^o)$$

The model also proposes that if the amount of ready-made food purchased (x_2) exceeds the quantity served (z_2), the difference represents FW, such that:

$$w_2 = (x_2 - z_2)$$

[1] The model assumes that the household technology and knowledge parameter (φ) is indistinct, either producing or handling food at home.

[2] Note that if purchased prepared food is for immediate consumption, $z_2 \cong x_2$ and $t_2 \cong 0$.

At the consumer level, FW (w_3) is determined by the difference between the total amount of food served in the household (z) and the total amount of food consumed (z_e), as follows: [3]

$$w_3 = (z - z_e)$$

Therefore, the total amount of FW (W) arising from household food production, handling of market-purchased ready-made food, and food consumption amounts to $w_1+w_2+w_3$. Consequently, the disutility of FW for an individual household (U_w) is given by:

$$U_w = U\ [\mathrm{W}\ (x_1, x_2); \gamma]^4,$$

Where γ represents an awareness parameter, ranging from 0 to 1, which scales the disutility of FW in the total individual utility function. If γ = 1, the consumer is fully conscious of FW, while if γ = 0, the consumer remains entirely oblivious to FW. For instance, when $\gamma = 0$, consumers derive their entire utility from food intake and display indifference to FW (Qi 2018). As a result, the combined utility function (UT) garnered from home-cooked food consumption, ready-made food consumption, and FW is denoted by:

$$U_T = U_{z_e} + U_w = U\ [G_1\ (x_1, t_1; \varphi), G_2\ (x_2, t_2; \varphi); \tau] + U\ [\mathrm{W}\ (x_1, x_2); \gamma].$$

Furthermore, the household faces a cash income constraint (I) derived from members' hourly wages (ω) earned by working hours (h) for pay, as well as from other income sources (V). The model also posits that individual households allocate non-wage hours to the purchasing and preparation of food inputs (t_1) and to the purchasing and handling of ready-to-eat foods (t_2). Consequently, the household's total time endowment (T) is:

$$T = t_1 + t_2 + h$$

Considering that consumers allocate their total income to purchase x_1 at a price of p_1 and x_2 at a price of p_2, the family income constraint is:

$$\mathrm{I} = \omega \cdot \mathrm{h} + \mathrm{V} = p_1 x_1 + p_2 x_2$$

Substituting $h = (T - t_1 - t_2)$ into the family income constraint equation and rearranging the terms, we obtain:

$$\omega T + \mathrm{V} = p_1 x_1 + \omega t_1 + p_2 x_2 + \omega t_2$$

Thus, a Lagrangian function (L) is used to maximize consumers' utility subject to a budget constraint as follows:

$$L = U\ [G_1\ (x_1, t_1; \varphi), G_2\ (x_2, t_2; \varphi); \tau] + U[\mathrm{W}\ (x_1, x_2); \gamma]+$$
$$\lambda\ (\omega T + \mathrm{V} - p_1 x_1 - \omega t_1 - p_2 x_2 - \omega t_2)$$

where λ represents the marginal utility of income. By solving the first-order conditions for x_1, x_2, t_1, t_2, and W, we obtain:

$$x_1 : U'_{z_1} G'_{1x_1} - \lambda p_1 = 0$$
$$x_2 : U'_{z_2} G'_{2x_2} - \lambda p_2 = 0$$
$$t_1 : U'_{z_1} G'_{1t_1} - \lambda \omega = 0$$
$$t_2 : U'_{z_2} G'_{2t_2} - \lambda \omega = 0$$
$$\mathrm{W}: U'_W - \lambda p_1 - \lambda p_2 = 0$$
$$\lambda : \omega T + \mathrm{V} - p_1 x_1 - \omega t_1 - p_2 x_2 - \omega t_2 = 0$$
$$\text{And } U'_{z_1} > 0,\ U'_{z_2} > 0,\ G'_{1x_1} > 0,\ G'_{2x_2} > 0,\ G'_{1t_1} > 0,\ G'_{2t_2} > 0,\ U'_W < 0.$$

Considering that:

- U'_{z_1} and U'_{z_2} are the marginal utilities of food intake z_1 and z_2, respectively;
- G'_{1x_1} and G'_{2x_2} are the marginal products of inputs x_1 and x_2, respectively;
- G'_{1t_1} and G'_{2t_2} are the marginal products of inputs t_1 in producing z_1, and inputs t_2 in producing z_2, respectively;
- And U'_W is the marginal disutility of FW.

[3] Ready-made foods that spoil before it becomes a meal are counted in w_2; all other non-eaten foods are considered w_3.
[4] The disutility of food waste is related to factors such as the loss of utility for not consuming available food, the monetary cost of lost food, the guilty feeling for wasting food, and environmental concerns. (Qi 2018)

By maximizing the conditions of the utility function, the general form of the implicit demand function for the inputs used in the model is (Huffman 2010):

$$x_i^* = D_{x_i}(p_1, p_2, \omega, V, \varphi, \tau, \gamma), i = 1,2$$
$$t_i^* = D_{t_i}(p_1, p_2, \omega, V, \varphi, \tau, \gamma), i = 1,2$$
$$W^* = D_W(p_1, p_2, \omega, V, \varphi, \tau, \gamma)$$

To maximize utility subject to a budget constraint, the individual household will rely indirectly on food input prices, ready-food prices, wage rates, other sources of income, and the parameters of technology, taste, and FW concern.[5]

4 Method of Analysis

4.1 The Data

A purposive-type sample was collected electronically from 04/26/2021 to 07/28/2021 using questionnaires distributed on social networks, mainly in home management groups on Facebook and WhatsApp. The survey garnered 511 usable responses from individuals living in Brazilian metropolitan regions, each of whom was at least 18 years old. These respondents predominantly took on the responsibilities of purchasing, managing, preparing, and disposing of food in their households. The research sought to compile data regarding the extent and regularity of household FW, demographic attributes of the participants, and their practices concerning food management and disposal at home.

The purposive non-probability sampling technique is effective when studying a specific cultural domain with knowledgeable individuals. However, the interpretation of the results is confined to the study (Tongco, 2007). In the current research, the purposive sample consisted of individuals engaged in home management groups on virtual social networks who reside in Brazilian metropolitan areas.[6]

4.2 The Variables

The dependent variable, FOOD, represents the average of two indicators related to the frequency and quantity of FW as shown in Table 1. The values of FOOD have been rounded to align with the 1 to 5 Likert scale.

Table 1.
Dependent variable definition

Variable	Definition
FOOD1	How often do you discard food at home? (never/seldom/sometimes/often/every day)
FOOD2	How much food do you discard at home? (none/few/medium/a lot/too much)
FOOD	[FOOD1 + FOOD2] /2

Table 2 showcases the independent variables utilized in the logistic regression. The variables CONCERN, LEFT, and PLAN are indexes constructed from observed variables detailed in the table. For the variable DISC1, respondents select from up to six reasons for discarding food, which include: food expired, food spoiled, dislike of food, food being poorly cooked, having one-day old leftovers, and having leftovers that are more than one day old. On the other hand, with the variable DISC2, respondents choose from up to ten food groups that they most frequently discard. These groups encompass cereal/grains, roots/tubers, beans/seeds, milk/dairy, meat/protein, fruit/vegetables, candy/dessert, drinks, compound dishes, and baking products.

4.3 The Empirical Model

The empirical model utilized was an ordered multinomial logit, which assumes a latent dependent variable y^* to represent both the amount and frequency of FW, as well as a vector x that comprises the independent variable determinants of FW. The econometric formulation is based on Mallick (2009) and is presented as follows:

$$y^* = x'\beta + \varepsilon$$

where β represents a vector of regression parameters and ε denotes the error term of the model. Given that y^* remains unobserved, we instead observe the Likert scale responses y with possible values of 1, 2, 3, 4, and 5, defined as follows:

[5] This theoretical model is based in Lima *et al.* (2024)
[6] Table A1 in the Appendix compares the model coefficients estimated using the full sample and a randomly drawn subsample of 30% for sample stability analysis.

$$y = j \text{ if } \mu_{j-1} < y^* \leq \mu_j$$

where *j* represents the ordered responses 1, 2, 3, 4, and 5, and μ_{j-1} are the *(J – 1)* unknown parameters that indicate the cut points or thresholds, such that:

$$0 < \mu_1 < \mu_2 < \mu_3 < \mu_4$$

Assuming ε is distributed as *N* (0,1), the probability of the *j-th* outcome can be defined as:

$$Prob(y = j) = \Phi(\mu_j - \mathbf{x}'\boldsymbol{\beta}) - \Phi(\mu_{j-1} - \mathbf{x}'\boldsymbol{\beta})$$

where Φ is a continuous and twice differentiable cumulative logistic distribution.

Table 2.
Independent variable definition

Variable	Definition
EDU	Number of years of formal education
AGE	Respondent's age
TOOLS	Kitchen´s equipment to avoid FW (none/few/medium/many/enough)
CONCERN	[CONCERN1+CONCERN2]/2
CONCERN1	Are you concerned about the problem of FW? (no/a little/medium/a lot/overly)
CONCERN2	Do you take measures to avoid FW? (never/seldom/sometimes/often/always)
READY	Purchase of ready-to-serve food (never/seldom/sometimes/often/every day)
BUYFOOD	For how many days do you buy food when you go shopping?
DISC1	Number of different reasons for discarding food (1 to 6 reasons).
INCOME	What is your monthly Gross Family Income? (in thousands of BRL);
DINCOME	0 for INCOME < 20000 BRL; 1 otherwise
MARRY	Marital status (0 Single/Separated/Divorced/Widowed; 1 Married/stable)
LEFT	[LEFT1+LEFT2] /2
LEFT1	Do you reuse leftovers from meals? (never/seldom/sometimes/often/every day)
LEFT2	Do you keep leftovers for more than a day? (never/seldom/sometimes/often/every day)
PLAN	[LIST+LABEL+STORE+MEALS] /4
LIST	Do you prepare shopping list? (never/seldom/sometimes/often/always)
LABEL	Do you check for food product dating? (never/seldom/sometimes/often/always)
STORE	Do you check food storage recommendations? (never/seldom/sometimes/often/always)
MEALS	Do you plan meals by the number of people? (never/seldom/sometimes/often/always)
PEOPLE	Number of individuals in the household
GENDER	Respondent´s gender? (0 Male; 1 Female);
SHOPTRIPS	How often do you go shopping for food? (never/seldom/sometimes/often/every day)
COOK	How often do you cook at home? (never/seldom/sometimes/often/every day)
CHECK	If not cooking, do you supervise the cooking? (never/seldom/sometimes/often/always)
DISC2	Number of different food groups frequently discarded (1 to 6 food groups).

This study **utilizes** the multinomial ordered logit model as defined by Greene (2002) and Mallick (2009), based on the formulation provided below.

$$logit[P(Y \leq j|x)] = \mu_j + \beta' x, j = 1, \cdots, J-1$$

where:

$Y = FOOD_i$,

$x_1{}' = (EDU_i,\ AGE_i, TOOLS_i, CONCERN_i, READY_i, BUYFOOD_i, DISC1_i)$

$x_2{}' = (INCOME_i,\ DINCOME_i, MARRY_i, LEFT_i, PLAN_i)$

$x_3{}' = (PEOPLE_i,\ GENDER_i, SHOPTRIPS_i, COOK_i, CHECK_i, DISC2_i)$

$i = 1,2, \cdots, n$ (n is the sample size)

and x_1, x_2 and x_3 are vectors of the explanatory variables used in Models 1, 2, and 3, respectively.

Model selection is based on various measures of goodness of fit, such as the statistical significance of the parameters, the Akaike Information Criterion (AIC), and the condition number of the Hessian (Cond.H). A smaller AIC is indicative of a superior fit since it correlates directly with the model's residual sum of squares (Enders 2015). The condition number of the Hessian represents the ratio of the largest to the smallest eigenvalues and signifies the empirical identifiability of the model. A “Cond.H” value below 10^6 suggests that the model has achieved a well-defined optimum.

5 Discussion of the Results.

5.1 Descriptive statistics

Table 3 displays the frequencies of the Likert-scale responses pertaining to the dependent variable FOOD, which represents the frequency and amount of FW. The data indicates that approximately 85% of respondents fall within levels 2 (almost never/a little) and 3 (sometimes/medium) of the Likert scale.

Table 3.
Dependent variable percentage of responses.

Variable\ Likert Scale	1	2	3	4	5
FOOD	6%	46%	39%	8%	1%

Table 4 presents a statistical summary of demographic data, including age, household size, education level, and income. The dataset indicates an average age of 42 years, pointing to a middle-aged demographic. It reflects the prevalence of middle-sized families in Brazil and a high level of education, evidenced by an average of 16 years of formal schooling. The average income is reported as eight times the Brazilian minimum wage. However, this is within a highly dispersed distribution, with incomes ranging from two to forty-two minimum wages. The sample's demographic profile shows that 74% of the individuals are women, and 53% are married. Consequently, the data suggest that the typical respondent is an educated, middle-aged woman, predominantly married and within the middle-income range.

Table 4.
Demographic characteristics of the respondents

Variables			
	Mean	**Minimum**	**Maximum**
AGE	42	18	81
PEOPLE	3	1	12
EDU	16	5	22
INCOME	8	2	41
	Men (0)		**Woman (1)**
GENDER	26%		74%
	Not Married (0)		**Married (1)**
MARRY	53%		47%

5.2 Logistic regression

The logistic regression model employed the dependent variable FOOD to characterize respondents' behavior concerning the frequency and quantity of FW. Three unique models were derived, each utilizing different sets of explanatory variables. The Akaike Information Criterion (AIC) was applied for model selection, and the condition number (Cond.H) was used to assess the empirical identifiability of the models. Table 5 displays the statistical outcomes of the ordered logistic regression for Model 1, including coefficient estimates, Percent Impacts (PI), and results of statistical tests.

All coefficients estimated for variables in Model 1 were statistically significant at p-values below 10%, and the condition number (Cond.H) indicated that the model was empirically identifiable. Interpreting these coefficients can be challenging, but it's possible to calculate the Odds Ratio (OR) by exponentiating the variable coefficients. To compute the Percentage Impact (PI) on the dependent variable due to a one-unit change in an explanatory variable, subtract the OR from one and express the result in percentage terms. [7] For instance, the variable EDU had an estimated coefficient of 0.054, leading to an OR of 1.056. Converting this into a percentage, the PI is 5.56%, reflecting an increase in the likelihood of Food Waste (FW) with each additional unit of education. Conversely, age had a negative impact on food waste, with a PI of -1.58%. These findings align with previous studies (van Geffen *et al.* 2016; Secondi *et al.* 2015). A unit increase in the values of variables TOOLS and CONCERN is associated with a PI decrease of 22.53% and 57.47%,

[7] UCLA: Statistical Consulting Group, 2021

respectively, supporting the notion that home technology and awareness about FW consequences are vital in reducing household FW (Cappelletti *et al.,* 2022; Comber and Thieme, 2012).

The variable READY, denoting the frequency of purchasing ready-to-eat foods, showed a positive PI of 43.44%. This aligns with Mallinson *et al.* (2016), who found that consumers of ready-to-eat foods tend to be less efficient in meal planning, contributing to FW. The variable BUYFOOD, reflecting family planning in food purchase amounts, exhibited a PI of -1.46% on FW. This supports the idea that planned shopping and inventory management can help reduce FW (Stefan *et al.* 2013). The variable DISC1, indicating the number of reasons for discarding food, had the most significant impact in the model, with a PI of 27% in FW odds. These reasons may include food safety concerns, which are known to increase FW according to Watson and Meah (2013).

Table 5.
Econometric results

VARIABLES	Estimates	Std. Error	P-value	PI (%)
		Model 1		
EDU	0.054	0.029	0.066	5.558
AGE	-0.016	0.006	0.012	-1.580
TOOLS	-0.255	0.086	0.003	-22.531
CONCERN	-0.854	0.155	0.000	-57.471
READY	0.361	0.108	0.001	43.438
BUYFOOD	-0.015	0.008	0.054	-1.466
DISC1	0.589	0.113	0.000	80.268
AIC 1019 / Cond.H 2.5e+05				
		Model 2		
INCOME	0.057	0.018	0.001	5.916
DINCOME	-1.497	0.618	0.015	-77.620
MARRY	-0.359	0.179	0.044	-30.186
LEFT	-0.577	0.107	0.000	-43.843
PLAN	-0.454	0.116	0.000	-36.547
AIC 1095 / Cond.H 3.1e+04				
		Model 3		
PEOPLE	0.109	0.055	0.049	11.493
GENDER	0.003	0.201	0.986	0.343
SHOPTRIPS	0.372	0.126	0.003	45.021
COOK	-0.192	0.087	0.027	-17.494
CHECK	-0.134	0.063	0.036	-12.506
DISC2	0.473	0.062	0.000	60.446
AIC 1095 / Cond.H 3.1e+04				

In Model 2, all variable coefficients were statistically significant at levels below 5%, and the condition number (Cond.H) suggestive of empirical identifiability. The variable INCOME, representing monthly gross family income, had a positive coefficient, aligning with findings in the literature (Zhang *et al.,* 2018). A dummy variable, DINCOME, defined as zero when INCOME is less than 20,000 BRL and one otherwise, was introduced to test if higher-income consumers are less inclined towards food waste than their lower-income counterparts. The negative coefficient of DINCOME implies that individuals with a gross monthly income exceeding 20,000 BRL are likely to decrease their food waste (FW) as their earnings increase. In terms of Percentage Impact (PI), a unit increase in monthly household income is associated with a 5.92% increase in the likelihood of FW. However, for higher-income individuals, this effect translates into a negative PI of -77.62%. These results corroborate the hypothesis that income's positive influence on FW reverses for higher-income groups (Setti *et al.,* 2016). The coefficient for the variable MARRY reveals that married respondents' families tend to waste less food compared to single ones, with a negative PI of -30.19%; this is consistent with Sunday *et al.* (2022). As anticipated, the variables LEFT and PLAN, representing leftover management and food planning, respectively, had negative coefficients. The PIs for these variables were -43.84% and -36.55%, supporting the notion that effective management of leftovers and planning of household food activities can substantially reduce FW (Romani *et al.,* 2018; Schanes *et al.,* 2018).

In Model 3, all variables except for GENDER showed statistical significance at p-values below 5%, and the condition number (Cond.H) affirmed the model's empirical identifiability. The lack of statistical significance for the GENDER variable's coefficient might be attributed to the high proportion of female respondents in the sample, approximately 75%. The estimated coefficients align with prior research on the direct influence of family size on Food Waste (Zhang *et al.,* 2018; Edjabou *et al.,* 2016). Specifically, the variable PEOPLE displayed a positive coefficient, resulting in a Percentage Impact (PI) of 11.49% on FW. The variable SHOPTRIPS, representing the frequency of food shopping, exhibited a positive relationship with FW, evidenced by a PI of 45.02%. Empirical studies suggest that increased shopping frequency can either mitigate or exacerbate FW, depending on whether it is part of efficient household management or driven by impulsive buying and poor planning (Jörissen *et al.,* 2015). The variables COOK (cooking at home) and CHECK (overseeing food preparation) were found to likely reduce FW. This reduction may be connected to improved cooking skills and vigilant kitchen management (Schanes *et al.,* 2018; Carroll *et al.,* 2021). The variable DISC2, denoting the number of discarded food groups, was positively associated with FW. A plausible explanation for this could be that a greater variety of foods complicates management, leading to increased waste (Thyberg and Tonjes, 2016).

6 Conclusions and Policy Implication

The Food and Agriculture Organization of the United Nations (FAO) estimates that globally, the food system discards a third of all food produced each year. This not only exacerbates food security issues but also signifies the wasteful allocation of resources meant for the production, processing, and distribution of unconsumed nutrients. Despite Brazil being a major global food producer, the 2020 Country Statistics Report highlighted that around 125 million people faced food insecurity, with 33 million suffering from severe hunger. Understanding the drivers of food loss and waste in the agri-food supply chain is thus imperative. This study focuses on household food waste (FW) in Brazilian metropolitan areas, aiming to inform policies that enhance food management and minimize food disposal.

The findings indicate that increasing levels of education and income tend to rise FW, although this trend reverses for higher-income households. Affluent consumers often purchase higher-value food products with longer shelf lives, thereby reducing food waste. Effective food management and reduction in FW can be achieved with proper knowledge and appropriate kitchen tools. The study's coefficient estimates suggest that concern for issues like hunger, environmental impact, and resource misuse is a significant deterrent to FW, influencing other variables. Furthermore, the degree of household meal planning, as indicated by various model variables, is crucial in curbing food disposal. The literature review concurs that efficient management of food preparation, from buying ingredients to managing leftovers, significantly cuts down on FW. Respondents who cited more reasons for discarding food often express heightened concerns about the effects of spoiled food on health and tend to waste more. Also, dietary diversification seems to lead to increased waste, as shown by a positive correlation between the variety of food groups consumed at home and FW.

However, correctly interpreting survey results is vital for deriving practical policy recommendations. Some findings directly inform FW reduction strategies. For instance, enhancing household food planning can substantially reduce FW. In terms of demographic variables and family characteristics, which are slower to change, survey insights are crucial for advising families to be more conscientious about FW. Policy implications for factors linked to increased FW, like diet diversification and health concerns about spoiled food, are more nuanced. It is not advisable to recommend reducing dietary variety or health concerns; instead, focusing on amplifying food-saving practices and tools appears more effective.

References

Abd Razak, S. (2017). Household food waste prevention in Malaysia: an issue processes model perspective [dissertation]. Tampa, Florida - USA: USF Tampa Graduate Theses and Dissertations.

AGROSTAT [Internet]. (2018). Estatísticas de Comércio Exterior do Agronegócio Brasileiro [Brazilian Agribusiness Foreign Trade Statistics]. Available from: https://indicadores.agricultura.gov.br/agrostat/index.htm

Annunziata, A., Muca, F.L., Mariani, A. (2022). Preventing household food waste in Italy: a segmentation of the population and suggestions for action. *Sustainability*, **14**(2): 7005.

Aschemann-Witzel, J., de Hooge, I., Amani, P., Bech-Larsen, T., Oostindjer, M. (2015). Consumer-related food waste: causes and potential for action. *Sustainability*, **7**(6): 6457–6477.

Becker, G.S. (1965). A theory of the allocation of time. *The Economic Journal*, **75**(299): 493.

Bretter, C., Unsworth, K.L., Russell, S.V., Quested, T.E., Doriza, A., Kaptan, G. (2022). Don't put all your eggs in one basket: testing an integrative model of household food waste. *Resources, Conservation and Recycling*, **185**: 106442.

Cappelletti, F., Papetti, A., Rossi, M., Germani, M. (2022). Smart strategies for household food waste management. *Procedia Computer Science*, **200**: 887–895.

Carroll, N., Sadowski, A., Parizeau, K., von Massow, M., Wallace, A., Jewell, K., Ma, D.W.L., Buchholz, A.C., Duncan, A.M., Chan, B., Haines, J. (2021). Food skills: associations with diet quality and food waste among Canadian parents. *Journal of Nutrition Education and Behavior*, **53**(5): 371–379.

Cecere, G., Mancinelli, S., Mazzanti, M. (2013). Waste prevention and social preferences: the role of intrinsic and extrinsic motivations. *SSRN Electronic Journal* [Internet]. 2013 Jun 3 [cited 2023 Jan 03]. Available from: https://doi.org/10.2139/ssrn.2273477.

Comber, R., Thieme, A. (2012). Designing beyond habit: Opening space for improved recycling and food waste behaviours through processes of persuasion, social influence and aversive affect. *Personal and Ubiquitous Computing*, **17**(6): 1197–1210.

Edjabou, M.E., Petersen, C., Scheutz, C., Astrup, T.F. (2016). Food waste from Danish households: generation and composition. *Waste Management*, **52**: 256–268.

Enders, W. (2015). Applied econometric time series. 4th ed. Hoboken, NJ: Wiley.

Fanelli, R. (2019). Using causal maps to analyse the major root causes of household food waste: results of a survey among people from central and southern Italy. *Sustainability*, **11**(4): 1183.

FAO (2011). Global food losses and food waste – extent, causes and prevention. [cited 2022 Dec 10]. Available from: https://www.fao.org/3/i2697e/i2697e.pdf.

FAO (2019). The state of food and agriculture: moving forward on food loss and waste reduction; [cited 2022 Dec 10]. Available from: https://www.fao.org/3/ca6030en/ca6030en.pdf.

FAO, IFAD, UNICEF, WFP, WHO (2022). The state of food security and nutrition in the world 2022. Repurposing food and agricultural policies to make healthy diets more affordable [cited 2022 Nov 10]: https://doi.org/10.4060/cc0639en.

Greene, W.H. (2002). *Econometric analysis* (5th ed.). Prentice Hall.

Hazuchova, N., Antosova, I., Stavkova, J. (2020). Food wastage as a display of consumer behaviour. *Journal of Competitiveness*, **12**(2): 51–66.

Heng, Y., House, L. (2022). Consumers' perceptions and behaviour toward food waste across countries. *International Food and Agribusiness Management Review*, **25**(2): 197–209.

Huffman, W.E. (2011). Household production theory and models. In: Jayson, L.L., Jutta, R., Shogren, J.F., editors. *The Oxford Handbook of the Economics of Food Consumption and Policy*. Online edition: Oxford Academic. pp. 34–74.

UCLA: Statistical Consulting Group (2021). Introduction to the features of SAS: SAS learning modules; [cited 2022 Aug 18]. Available from: https://stats.oarc.ucla.edu/sas/modules/introduction-to-the-features-of-sas.

Jörissen, J., Priefer, C., Bräutigam, K.-R. (2015). Food waste generation at household level: results of a survey among employees of two European research centers in Italy and Germany. *Sustainability*, **7**(3): 2695–2715.

Karunasena, G.G., Ananda, J., Pearson, D. (2021). Generational differences in food management skills and their impact on food waste in households. *Resources, Conservation and Recycling*, **175**: 105890.

Kavanaugh, M., Quinlan, J.J. (2020). Consumer knowledge and behaviours regarding food date labels and food waste. *Food Control*, **115**: 107285.

Landry, C.E., Smith, T.A. (2017). Household food waste: theory and empirics. *SSRN Electronic Journal*, [updated 2018 Sep 22; cited 2022 Dec 10]. Available from: https://doi.org/10.2139/ssrn.3060838.

Li, C., Bremer, P., Harder, M.K., Lee, M.S.W., Parker, K., Gaugler, E.C., Mirosa, M. (2022). A systematic review of food loss and waste in China: quantity, impacts and mediators. *Journal of Environmental Management*, **303**: 114092.

Lima, R., Yu, A., Liu, Q., et al. (2024). Examining the determinants of food waste behavior in China at the consumer level. *Food Security*, **16**: 867–881. https://doi.org/10.1007/s12571-024-01466-9.

Lusk, J.L., Ellison, B. (2016). A note on modelling household food waste behaviour. *Applied Economics Letters*, **24**(16): 1199–1202.

Mallick, D. (2009). Marginal and interaction effects in ordered response models. MPRA-Munich Personal RePEc Archive. [cited 2022 Dec 10]. Available from: https://mpra.ub.uni-muenchen.de/13325/.

Mallinson, L.J., Russell, J.M., Barker, M.E. (2016). Attitudes and behaviour towards convenience food and food waste in the United Kingdom. *Appetite*, **103**: 17–28.

Martins, M.R., Viana, L.F., Cappato, L.P. (2022). Food waste profile in Brazilian food and nutrition units and the implemented corrective actions. *Food Science and Technology* [Internet], [cited 2022 Dec 10]; 42. Available from: https://doi.org/10.1590/fst.100421.

Mattar, L., Abiad, M.G., Chalak, A., Diab, M., Hassan, H. (2018). Attitudes and behaviours shaping household food waste generation: lessons from Lebanon. *Journal of Cleaner Production*, **198**: 1219–1223.

Porpino, G., Lourenço, C.E., Araújo, C.M., Bastos, A. (2018). Intercâmbio Brasil – União Europeia sobre desperdício de alimentos. Relatório final de pesquisa. Brasília: Diálogos Setoriais União Europeia – Brasil. Available from: http://www.sectordialogues.org/publicacao [cited 2022 Nov 02].

Principato, L., Secondi, L., Pratesi, C.A. (2015). Reducing food waste: an investigation on the behaviour of Italian youths. *British Food Journal*, **117**(2): 731–748.

Qi, D., Roe, B.E. (2016). Household food waste: multivariate regression and principal components analyses of awareness and attitudes among U.S. consumers. PLOS ONE, **11**(7): e0159250.

Qi, D. (2018). Three essays on the economics of food waste [dissertation]. Ohio: Ohio State University.

PENSSAN (2022). II Inquérito Nacional sobre Insegurança Alimentar no Contexto da Pandemia da COVID-19 no Brasil. São Paulo. Available from: https://olheparaafome.com.br/wp-content/uploads/2022/06/Relatorio-II-VIGISAN-2022.pdf [cited 2022 Nov 02].

Romani, S., Grappi, S., Bagozzi, R.P., Barone, A.M. (2018). Domestic food practices: a study of food management behaviours and the role of food preparation planning in reducing waste. *Appetite*, **121**: 215–227.

Schanes, K., Dobernig, K., Gözet, B. (2018). Food waste matters - A systematic review of household food waste practices and their policy implications. *Journal of Cleaner Production*, **182**: 978–991.

Secondi, L., Principato, L., Laureti, T. (2015). Household food waste behaviour in EU-27 countries: A multilevel analysis. *Food Policy*, **56**: 25–40.

Setti, M., Falasconi, L., Segrè, A., Cusano, I., Vittuari, M. (2016). Italian consumers' income and food waste behaviour. *British Food Journal*, **118**(7): 1731–1746.

Stefan, V., van Herpen, E., Tudoran, A.A., Lähteenmäki, L. (2013). Avoiding food waste by Romanian consumers: The importance of planning and shopping routines. *Food Quality and Preference*, **28**(1): 375–381.

Sunday, C.O., Sowunmi, F.A., Obayelu, O.A., Awoyemi, A.E., Omotayo, A.O., Ogunniyi, A.I. (2022). Disentangling drivers of food waste in households: Evidence from Nigeria. *Foods*, **11**(8): 1103.

Talwar, S., Kaur, P., Okumus, B., Ahmed, U., Dhir, A. (2021). Food waste reduction and taking away leftovers: Interplay of food-ordering routine, planning routine, and motives. *International Journal of Hospitality Management*, **98**: 103033.

Thyberg, K.L., Tonjes, D.J. (2016). Drivers of food waste and their implications for sustainable policy development. *Resources, Conservation and Recycling*, **106**: 110–123.

Tongco, M.D. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications*, **5**: 147.

UNEP (2021). Food waste index report 2021. Available from: https://wedocs.unep.org/20.500.11822/35280 [cited 2022 Oct 02].

van Geffen, E.J., van Herpen, H.W.I., van Trijp, J.C.M. (2016). Causes & determinants of consumers' food waste: Project report, EU Horizon 2020 REFRESH. Wageningen University and Research. Available from: https://eu-refresh.org/sites/default/files/Causes%20&%20Determinants%20of%20Consumers%20Food%20Waste_0.pdf [cited 2022 May 30].

van Herpen, E., van Geffen, L., Nijenhuis-de Vries, M., Holthuysen, N., van der Lans, I., Quested, T. (2019). A validated survey to measure household food waste. *MethodsX*, **6**: 2767–2775.

Visschers, V.H.M., Wickli, N., Siegrist, M. (2016). Sorting out food waste behaviour: A survey on the motivators and barriers of self-reported amounts of food waste in households. *Journal of Environmental Psychology*, **45**: 66–78.

Watson, M., Meah, A. (2012). Food, waste and safety: Negotiating conflicting social anxieties into the practices of domestic provisioning. *The Sociological Review*, **60**(suppl 2): 102–120.

WHO [Internet] (2021). UN report: Pandemic year marked by spike in world hunger. Available from: https://www.who.int/news/item/12-07-2021-un-report-pandemic-year-marked-by-spike-in-world-hunger [cited 2022 Apr 21].

Xue, L., Liu, G., Parfitt, J., Liu, X., Herpen, E., Stenmarck, A., O'Connor, C., Östergren, K., Cheng, S. (2017). Missing food, missing data? A critical review of global food losses and food waste data. *Environmental Science and Technology*, **51**: 6618–6633.

Zhang, H., Duan, H., Andric, J.M., Song, M., Yang, B. (2018). Characterization of household food waste and strategies for its reduction: A Shenzhen city case study. *Waste Management*, **78**: 426–433.

Appendix

Table A1.
Comparison of Model Coefficients and Statistical Significance between full sample and 30% subsample

VARIABLES	**Full Sample**		**Subsample**	
Model 1	**Estimat**	**P-value**	**Estimates**	**P-value**
EDU	0.054	0.066	-0.007	0.907
AGE	-0.016	0.012	-0.026	0.037
TOOLS	-0.255	0.003	-0.217	0.162
CONCERN	-0.854	0.000	-0.933	0.001
READY	0.361	0.001	0.230	0.262
BUYFOOD	-0.015	0.054	-0.032	0.022
DISC1	0.589	0.000	0.587	0.001
Model 2	**Estimates**	**P-value**	**Estimates**	**P-value**
INCOME	0.057	0.001	0.010	0.756
DINCOME	-1.497	0.015	0.225	0.831
MARRY	-0.359	0.044	-0.358	0.270
LEFT	-0.577	0.000	-0.580	0.002
PLAN	-0.454	0.000	-0.449	0.029
Model 3	**Estimates**	**P-value**	**Estimates**	**P-value**
PEOPLE	0.109	0.049	0.358	0.001
GENDER	0.003	0.986	-0.182	0.609
SHOPTRIPS	0.372	0.003	0.558	0.016
COOK	-0.192	0.027	-0.304	0.042
CHECK	-0.134	0.036	-0.027	0.825
DISC2	0.473	0.000	0.548	0.000

As part of the sample stability analysis for the empirical models, a subsample of size 153 (one-third of the total) was randomly drawn from the full sample, and the models were re-estimated. Most coefficient signs remain consistent between the full sample and the subsample, except for EDU in Model 1 and DINCOME in Model 2, where signs change. The subsample tends to have fewer significant variables, possibly due to its smaller size, reducing statistical power. Some variables lose significance, such as TOOLS in Model 1 and MARRY in Model 2, while others, like BUYFOOD in Model 1, become significant in the subsample. Overall, the sample and subsample exhibit similar characteristics.