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Exploring the Relationship between Household Food Waste and Potential Predictors among Rotterdam Residents

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Summary

"It is estimated that one third of the food produced for human consumption is lost or wasted" (World Food Programme, 2020). In the past decades, the unprecedented scale of food waste has become a sustainability issue that is in dire need of addressing as it has been linked to a multitude of social, environmental, and economic issues. Food loss is occurring in every part of the global food supply chain. However, food waste has been linked primarily to the consumer spectrum in developed countries. The Netherlands has been rated amongst the worst European countries for household food waste (Seveno, 2022). The city of Rotterdam, specifically, reported having 94 kg of household food waste annually (Langeveld, 2018). This reality indicates a severe problem in the consumer behavior and waste management of the municipality. Previous literature primarily measures household food waste by measuring behavior/s that increase or decrease food waste, and the effect of awareness interventions on these factors. The present study examines the relationships between household food waste and relevant predictors: food waste behaviors, food waste awareness, and sociodemographic factors. This study adapted the Stimulus Organism Response to develop a theoretical concept to measure the predictors. The study is spatially bound to Rotterdam residents of Struisenberg, Kralingen. The quantitative nature of this study adopts one method of primary data collection: the survey. The data collected 361 respondents and used statistical analysis namely descriptive, correlation and multiple regression to discuss the findings. The outcome of the analysis is that food waste behavior has the strongest relation and predictive ability to measure household food waste. It is inconclusive the extent to which the food waste awareness or sociodemographic factors measured have a similar effect, though the research found six factors influence considerably more. This study does not attempt to provide definitive statements, but rather aid to academic and societal discourse. The interpretations of this research argue that to address household food waste in Rotterdam, more funding, educational campaigns, and census data collection need to be executed.

Keywords

Household Food Waste, Consumer Behavior, Food Waste Awareness, Rotterdam, Waste Management, Urban Management and Development

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1. Chapter 1: Introduction

1.1. Background

Rotterdam is a thriving cosmopolitan city known for its modernity and innovation. As the second-largest populated city in the Netherlands, home to more than 655,000 inhabitants, the city has continued projections to grow. By 2030, Rotterdam, the Hague, Amsterdam, and Utrecht are projected to contain roughly three-quarters of the Dutch population (Yan, 2019). With the rapid urbanization of the city, alongside the effects of climate change, Rotterdam is vulnerable to a multitude of environmental and socioeconomic problems. In lieu of the country's ambitious goals to have a 50% reduction in raw materials consumption and to become a waste-free economy by 2050, Rotterdam has increased pressure to commit and implement circular economy practices as soon as possible (European Environmental Agency, 2020).

Among the various challenges anticipated for Rotterdam, food waste emerges as a rectifiable problem. Food waste has become a major global problem that is affiliated with significant economic, environmental, and social consequences. Research from 2020 placed the Netherlands as the fifth worst European country for food waste, revealing that individuals in the Netherlands wasted 161 kilograms of food, which was significantly higher than the European average of 127 kilograms per capita (Seveno, 2022). Out of the 161 kilograms, almost 40% of the food waste occurred at the household consumer level. While the municipality, private companies, and nonprofit organizations have started a wide range of initiatives to encourage sustainable consumer habits, a significant amount of food is still being wasted in the city of Rotterdam.

The city of Rotterdam produces 10 million kilograms of household food waste annually (Iman, 2021). Given the projections of growing overpopulation, a larger amount of total household waste will be produced. Rotterdam residents, in particular, have been reported to waste 94 kilograms of food per year, and it is estimated that about one-third of the food bought is lost (Langeveld, 2018). These statistics suggest poor food waste habits, poor food waste management, and a deep-seated necessity for circular economy practices.

Food waste at the household level occurs when food spoils and is thrown away, or when edible food is intentionally discarded. Throwing away organic matter in landfills has become increasingly harmful due to failed aerobic decomposition. For organic matter to break down properly, microorganisms need oxygen, and when organic matter is dumped in landfills, it is buried beneath a significant amount of other waste, meaning that the necessary oxygen for aerobic decomposition to occur is deprived (Hu, 2020). When this process is so heavily hindered, biogas is created as a by-product. Biogas is 50% methane and 50% carbon dioxide and is one of the most potent greenhouse gases that contribute to global warming and climate change. Methane traps 28-36 times more heat in the atmosphere than carbon dioxide (Hu, 2020). Some countries have begun to account for this phenomenon by implementing a methane capture system in their landfills, however, these systems cannot capture all the gas released. By proxy, landfills remain one of the world's largest sources of greenhouse gas emissions (Hu, 2020).

In the Netherlands, if the municipality of the city has provided a green bin, organic waste should be disposed of there. If there is no bin available, the waste should be taken to a nearby collection facility. However, in 2006, the Rotterdam municipality decided to limit the number of green bins around the city to increase the number of paper recycling bins under the premise that it is more worthwhile, sustainable, and profitable (Langeveld, 2018). Research has shown that residents struggle to separate or dispose of their organic waste due to the lack of accessibility of green bins provided (Design Innovation Group, 2015). In densely populated urban areas, organic waste continues to be a large problem because it is considered substantially more difficult to separate than other recyclable waste as it is wet, dirty, and smelly (Yan, 2019). This reality is a step back in the city's efforts to implement circular economy practices and should be considered as the city navigates towards becoming waste free.

1.2. Aims of Research

The aim of the research was twofold. The first was to be academically relevant. The second was to inform the discourse surrounding food waste management in Rotterdam.

The study of waste management falls within Urban Management and Development, a multidisciplinary field that engages social sciences and humanities. Previous studies have focused on investigating the effects of increased awareness of reducing food waste, other indicators encouraging food waste, and other methods to prevent food waste through food production. There has been widespread data collection on countries all around the world, and even specific cities. Studies done in the Netherlands have been focused on household waste in general (Vanham, Mak, & Gawlik, 2016), consumer behavior in stores on household food waste (Janssens, Lambrechts, Osch, & Semeijn, 2019), and what specific foods are being wasted by consumers at the household level (van Dooren, Janmaat, Snoek, & Schrijnen, 2019). The first aim of this research was to address knowledge gaps concerning the potential predictors of household food waste.

The disposal of organic matter in a secure fashion is a mendable dilemma. To mitigate the biogas created from the inappropriate disposal of organic matter, collective action is necessary. Solutions such as educational campaigns and composting schemes require resources, time, funding, and civic engagement. The second aim is that findings could provide relevant stakeholders, municipalities, private companies and nonprofit organizations, insights on how to allocate resources to combat this problem.

1.3. Scope of Research

The scope of this research was confined to investigating what are the predictors of household food waste in Rotterdam. Due to the constricted timeframe of this study, the research was confined to a single neighborhood in Rotterdam: Struisenberg, Kralingen. To decide on the relevant or potential predictors used in this study, the researcher conducted an extensive literature review.

The proposed predictors (independent variables) in this study are food waste behaviors, food waste awareness, and sociodemographic factors. They were measured against self-reported household food waste (dependent variable). A survey was used to collect data on the independent and dependent variables for 361 residents of Struisenberg. The researcher used a consumer psychology theory (SOR) and statistical analysis including descriptive analytics, correlation, and multiple regression to further understand the relationships.

For the purpose of this study, the researcher chose four food waste behaviors: planning meals in advance, over-purchasing food, storing food improperly, and confusion about expiration dates. The scope of food waste awareness was approached through pillars and dimensions. The four pillars were social, environmental, economic, and water-related negative externalities of household food waste. The three dimensions were related to each pillar: perceived importance, knowledge about, and intent to change behavior. The sociodemographic factors included: age, gender, nationality, level of education completed, number of people per household, if the household included children and accessibility to compost bin.

1.4. Research Questions

Main Research Question

To what extent do food waste predictors influence household food waste in Rotterdam?

Sub Questions

1. To what extent do food waste behaviors influence household food waste?
2. To what extent does food waste awareness influence household food waste?
    a. Do pillars influence household food waste?
    b. Do awareness dimensions influence household food waste?
3. To what extent do socio-demographic factors influence household food waste?

1.5. Thesis Reading Guide

This study is organized into five chapters. Chapter 2 offers an extensive literature review of the key academic theories and concepts used in the study. Chapter 3 presents the methodology chosen, and outlines the statistical analysis used in the study. Chapter 4 consists of the results and discusses the key findings of the study. Finally, chapter 5 concludes the research and offers recommendations for future research considering household food waste.

2. Chapter 2: Literature Review & Theoretical Concepts

This chapter reviews existing academic literature and industry reports to provide context for the subjects and methodology of this research. The first section defines relevant concepts, namely: sustainability, circular economy and food security; while the second defines food waste implications. A section on each of the proposed potential predictors, behavior, awareness and sociodemographic, summarizes existing research. The sixth section explored relevant theoretical frameworks which informed the development of the conceptual framework used for this study.

2.1. Relevant Concepts

2.1.1. Sustainability

Sustainability was first defined by the United Nations Brundtland Commission as “meeting the needs of the present without compromising the ability of future generations to meet their own needs” (1987). Sustainability entails the protection of the *environment* and natural resources while simultaneously providing *social* and *economic* welfare to the present and future generations; the three pillars of sustainability (Hansmann, Mieg, & Frischknecht, 2012). The pursuit of sustainability has evolved to holistically address the complex multidimensional interest of multilateral stakeholders (Scoones, 2007)

There are 17 Sustainable Development Goals (SDGs) signed by the 191 member states of the United Nations, these include 169 targets to be achieved by the year 2030 (Yinuo, 2023). Of these SDGs, SDG 11: make cities inclusive, safe, resilient, and sustainable, highlights the complexity of urban development.

The population density of the world today demonstrates the necessity for a peculiar focus on urban planning: more than half of the world’s population lives in urban areas, it is expected this number will increase by 68% by 2050 (United Nations, 2018). Projections show that urbanization comes alongside a monumental number of problems by itself such as high population density, inadequate infrastructure, lack of affordable housing, flooding, pollution, slum creation, crime, congestion, and poverty (Kuddus, Tynan, & McBryde, 2020). Poorly planned urbanization increases inequality within cities that have economic, spatial, and social dimensions. While the world continues to urbanize, sustainable development depends on the successful management of urban growth, ensuring access to infrastructure, housing, education, health care, and a sustainable environment for everyone (United Nations, 2018).

2.1.2. Circular Economy

A circular economy, as opposed to a linear economy, is depicted as a sustainable economy system wherein economic growth is disassociated from resource extortion and dependent on the reduction and recirculation of natural resources (Corona, Shen, Reike, Rosales Carreón, & Worrell, 2019). The concept has gained momentum with the European Commission, who has embedded the theory into sustainable development policies (Corona et. al, 2019). The concepts of these strategies develop through "sustainable and eco-design, energy and material efficiency measures, strategies entailing the three-Rs of waste (reduce-reuse-recycle), business model innovation, industrial symbiosis, and so forth" (Corona et. al, 2019). Preserving the value of products in the economy, such as organic matter, has been recognized to benefit not only the environment but also industry and civil society.

An ideal way to mitigate food waste through a circular economy is adopting composting. Composting has many environmental and economic benefits but is not always considered a method of reducing food waste because the impurities of food are widely distributed and centralized composting facilities are not efficient in disposing of them. Many governments may not be able to provide a domestic composting device to its residents (Zhou et al., 2020). Many cities in the world are attempting to advance towards a circular economy for its many benefits towards waste management and pollution. It is crucial to consider that without meaningful synergies between local, regional, and national governments, as well as international or nongovernmental actors, the transition is made extremely difficult (Vergara & Jammi, 2022). Not only does the transition require financial mobilization to implement but collaboration with all actors, including civil society. To this degree, it is essential to include the public in the process to encourage the addition of circular economic practices in their day-to-day lives.

2.1.3. Food Security

Food security as defined by the World Bank in 1986 is "access by all people at all times to enough food for an active, healthy life". Food security at a household level is usually perceived as the number of food-production resources available to them, the income available for food purchasing, and reaching the minimum nutritional requirements. A variety of factors may influence food security at a household level such as the food market prices, transportation networks and storage facilities, weather or other environmental factors, forms of food rationing, and so forth (Chen & Kates, 1994). Food security at a national level is usually perceived as the ability to meet the food requirements of the entire population while assuming equal access to all social classes (Chen & Kates, 1994). By this frame of reference, global food security is the ability of every country to provide its own national food security.

The current food production levels must urgently increase with the global population, as the global population is projected to exceed 9 billion by 2050 (Tyczewska, Woźniak, Gracz, Kuczyński, & Twardowski, 2018). The amount of available land for farming has shrunk as the rate of erosion and pollution has increased. Furthermore, the loss of arable land has also accelerated due to heavy fertilization and chemical supplementation. Finally, climate change has become a testament to the decline of agricultural productivity due to the increase in extreme temperatures and weather events (Tyczewska et. al, 2018).

A representative example of a world that encapsulates food security is where it produces enough food for the entire population while also providing equal access. To meet these requirements there must be no famine, malnutrition, micronutrient deficiencies, and nutrient-depleting illnesses (Chen & Kates, 1994). Estimations envision a hungry population of "641 million in 2060 under the current climate, and 629 million with climate change projections" (Chen & Kates, 1994). These projections involve 'business as usual' scenarios wherein the complexity of food security has not yet been acknowledged or dealt with accordingly.

The existing food production is also perceived as unequally managed and distributed. Reports by the United Nations show that nearly 98% of the people identified as suffering from food insecurity reside in developing countries (Otero, Gürcan, Pechlaner, & Liberman, 2018). However, even wealthy countries have populations suffering from food security and encounter growing rates of malnutrition. Food security also requires a concentrated review of the link between class inequality and access to sufficient and healthy food. Urban governance then plays an important role in addressing social inequality in terms of food production and distribution, implementation of affordable nutritional choices that are environmentally sustainable is becoming even more critical (Otero et. al, 2018).

2.1.4. Food Waste Implications

The term 'food loss' describes the "food that was originally intended for human consumption but has been devalued due to various factors at the stage of production, harvest, and processing". The term 'food waste' is characteristic of the later stages of the food chain, the consumption in households wherein food is discarded that has not been eaten, spoiled, or considered inedible (Seberini, 2020). Research has shown that food loss occurs mostly in developing countries, while food waste is especially critical in developed countries (Seberini, 2020; Aschemann-Witzel, de Hooge, Amani, Bech-Larsen, & Oostindjer, 2015). Furthermore, it is estimated that in developed countries up to “40% of food waste occurs in households, which is ten times more than in developing countries” (Seberini, 2020). Research has found that food wastage at the consumption level has been primarily linked to middle-class and higher-income households (Reisch, Eberle, & Lorek, 2013). Roughly a total of 1.3 billion tons of food produced for human consumption is lost or wasted per year (Schanes, Dobernig, & Gözet, 2018). This statistic portrays the variety of severe social, environmental, and economic consequences.

The link between food wastage and climate change has become increasingly recognized as posing large threats to both the environment and public health. Food production is resource-intensive; therefore, it indirectly influences a large number water of environmental impacts such as social erosion, deforestation, water, and air pollution, furthermore there are substantial greenhouse gas emissions at all stages of the food cycle (Schanes, Dobernig, & Gözet, 2018). Roughly 45 trillion gallons of water are lost every year due to food waste, which equivalates to 24% of all water used for agriculture (Barclay, 2013). The creation of biogas is a direct consequence of household food waste, but in addition to the other implications, food waste is a major environmental problem.

In the context of food security, part of the population has sufficient or surplus access to food, however another part of the population does not have fair access to quality food or any food at all. Research demonstrates that 50% of edible food is discarded unnecessarily in European homes, supermarkets, and restaurants every year, while roughly 16 million people depend on food aid every year (Seberini, 2020). These social inequalities determine the necessity for equal distribution of food, and minimization of food waste.

Globally, the economic value of food wasted is approximately 1,000 billion USD annually (Seberini, 2020). Food waste in developed countries can be closely associated with influencing demand, which leads to an escalation in the price level of food stocks, not to mention inflation rates (Seberini, 2020). This can influence inequality as people with lower incomes may not be able to afford food. Economically speaking, both producers and consumers are integral components of the existing economic system and engage consecutively (Seberini, 2020). Consumer preferences influence the behavior of food producers. The economic system operates in a highly intricate manner: the utilization of resources is contingent not only upon production techniques and distribution but also on the final consumption which is multiplied by population size. It is therefore impractical to attempt to separate production from consumption, even the ordinary consumer assumes responsibility for the environmental consequences associated with their food waste.

Food waste has been increasingly acknowledged as an urgent issue among governments, businesses, NGOs, academics, and the public. It is an issue that needs to be addressed at every stage of the food cycle of production, distribution, and consumption. Nonetheless, private households represent the largest food-waste faction (Schanes, Dobernig, & Gözet, 2018). This is why academia has had a widespread focus on both the evaluation of consumer habits and awareness with respect to food consumption and waste generation, and the valorization of non-preventable waste or how to change waste streams onto economic value (Morone, Koutinas, Gathergood, Arshadi, & Matharu, 2019).

Food waste research mainly focuses on either measuring the quantity of food wasted or understanding consumers' beliefs, attitudes, and motivations that lead to food waste behavior (Aydin & Yildirim, 2021). It also pertains to what forms of intervention can raise awareness of food waste and how interventions may change behavior on food waste. Food waste occurring at the household level requires a focus on the understanding of consumer behavior to be useful for prevention.

2.2. Food Waste Behaviors

Previous literature determined specific behaviors that influence food waste as over-purchasing of food, improper storage of food, and cooking skills to use leftover food and ingredients (Ananda, Karunasena, Mitsis, Kansal, & Pearson, 2021; Archip, Banatean-Dunea, Petrescu, & Petrescu-Mag, 2023; Quested, Marsh, Stunell, & Parry, 2013; Hebrok & Boks, 2017; Ponis, Papanikolaou, Katimertzoglou, Ntalla, & Xenos, 2017; Quested, Marsh, Stunell, & Parry, 2013; Principato, Mattia, Di Leo, & Pratesi, 2020; Roodhuyzen, Luning, Fogliano, & Steenbekkers, 2017; Gjerris & Gaiani, 2013).

Furthermore, studies determined behaviors such as planning meals before shopping and confusion about expiration dates to influence food waste (Ponis et. al, 2017; Hebrok & Boks, 2017; Quested et. al, 2013; Principato et. al, 2020; Carolan, 2021; Block et al., 2016).

Apart from simply throwing away edible food, the aforementioned studies determine that the main behaviors that increase food waste are over-purchasing of food, improper storage of food, cooking skills and use of leftovers, planning meals in advance, and confusion over expiration dates. The overarching theme of these studies is that food waste behavior is not limited to throwing away edible food, these other determinants result in higher or lower household food waste. For instance, planning meals in advance and purchasing only the necessary amount of food for your household consumption, results in a substantially lower amount of food waste. Simultaneously, people who do not have sufficient cooking skills to make use of leftovers or their ingredients waste more food than those who do. Furthermore, people who do not properly store their food or get confused about expiration dates end up throwing away more food than those who do. All these behaviors result in increased or decreased food waste, and therefore for the purpose of this study will be used as indicators of food waste behaviors.

2.3. Food Waste Awareness

Food waste behavior research concludes the necessity for specified interventions and awareness techniques to reduce food waste. Food waste awareness is about increasing the amount of knowledge on the negative consequences of food waste socially, economically, and environmentally.

2.3.1. Prior Research

Studies relating to food waste awareness have been primarily focused on intervention strategies and their influence on reducing food waste. Researchers often introduce an intervention strategy such as a campaign, and then measure its effectiveness in reducing food waste.

A study done in Romania showed that awareness campaigns had a positive impact on both self-assessed food waste and actions taken to prevent it (Chinie, Biclesanu, & Bellini, 2021). Another study in Canada found that different forms of awareness educational campaigns can have positive results in reducing food waste behaviors such as community engagement and gamification (Soma, Li, & Maclaren, 2020). Another study focused on the impact of purchasing near-expired food campaigns and found that the message about food waste avoidance increased consumers' willingness to buy near-expired food through moral satisfaction and awareness (Zhang, van Herpen, Van Loo, Pandelaere, & Geuens, 2023). Another study performed in Norway and Sweden aimed to use smartphone apps as a form of awareness intervention in food waste, they found that apps were effective in reducing personal food waste and improving dietary habits, also that the participants reported saving money using the apps (Mathisen & Johansen, 2022). A study in Poland found that nutritional awareness campaigns increased the likelihood that participants make healthier food choices and reduce their food waste (Nicewicz & Bilska, 2022).

Campaigns performed in the United Kingdom, Japan, Denmark, and Hong Kong had positive results in diminishing food waste behaviors at the household level (Shaw, Smith, & Williams, 2018; Zhang, van Herpen, Van Loo, Pandelaere, & Geuens, 2023; Halloran, Clement, Kornum, Bucatariu, & Magid, 2014). These campaigns ignite the necessity for education and raising awareness to combat the negative consequences of food waste at the household level. Researchers conclude that consumers can become smart buyers, learning to avoid economic and environmental waste by being educated on appropriate storage methods and grocery purchase planning (Zamri et al., 2020). Furthermore, research has concluded that sustainable behavior could be conditioned such as the recycling of organic waste through informational campaigns, with participants stating that there should be more promotion of environmental awareness (Pinto, Pinto, Melo, Campos, & Cordovil, 2018).

2.3.2. Awareness of Food Waste Implications

Prior research has mainly focused on raising awareness of implications through intervention strategies. Comparably, many studies have focused on measuring existing awareness of implications and how much this may influence household food waste (Graham-Rowe, Jessop, & Sparks, 2014; Reynolds et al., 2019; Neff, Spiker, & Truant, 2015; Ilakovac, Cerjak, & Voca, 2020). These studies also measured food waste behaviors and how they were affected by awareness. Prior research on food waste mainly calls for awareness to prevent household food waste but does not include what the awareness of the participants may already be. In consideration of the time frame of this study, the researcher proposed doing a study based on measuring awareness of implications rather than implementing an intervention and measuring it.

2.4. Other Predictors of Food Waste

Previous researchers on food waste behavior have found a variety of reasoning behind why people waste food all over the world. Researchers identified specific behaviors that contribute to more food waste in households, demographic factors that may influence food waste in households more than others, and highlighted how cultural differences may play a role in food waste.

2.4.1. Demographic Factors as a Food Waste Predictor

Previous literature has concluded that alongside several of the specific behaviors cited above, there is also a range of demographic factors that influence food waste such as age, income, educational level, and household size (Roodhuyzen, Luning, Fogliano, & Steenbekkers, 2017; Fami, Aramyan, Sijtsema, & Alambaigi, 2019; Li, Jiang, & Qing, 2023; Gjerris & Gaiani, 2013). A study that included all 27 European Union member states discovered that households with higher income levels tend to waste more food than lower income levels and that households with children tend to waste more food than those without children (Secondi, Principato, & Laureti, 2015). Another study also determined that households with children generate more household food waste than those without children, furthermore that households with more members tend to generate more food waste than smaller households (Gjerris & Gaiani, 2013). Therefore, it is useful to use sociodemographic factors to further explain food waste behaviors and levels of awareness.

2.4.2. Culture influencing Food Waste

Many researchers determined food waste-specific behaviors as cultural factors that influence food waste, however, some found that specific personal preferences could influence food waste further. A study in Italy determined that consumers' behaviors towards food waste can be based on their attitudes such as they waste food because it does not smell or look good, they forget about the food, or over-purchasing food (Gaiani, Caldeira, Adorno, Segrè, & Vittuari, 2018). Other studies highlighted how specific brand packaging and personal preference played a role in food waste (Roodhuyzen, Luning, Fogliano, & Steenbekkers, 2017; Hebrok & Boks, 2017; Block et al., 2016). An extensive literature review found that alongside specific behaviors of over-purchasing, improper storage, and confusion about expiration dates, cultural norms about portion sizes were the main factor that contributed to food waste (Quested, Marsh, Stunell, & Parry, 2013).

2.4.3. External Influences

External influences such as the COVID-19 pandemic have also been proven to influence food waste behavior. A study in Brazil during the COVID-19 pandemic showed significant behaviors such as intention to reduce food waste, routines for purchasing food on sale, and routines for handling leftovers increased (Schmitt, Cequea, Neyra, & Ferasso, 2021). Another study in Australia showed that households reduced their food waste by 9% post-COVID-19 because they changed their grocery shopping and storing behaviors, with more households buying in bulk and storing food for longer periods of time (Ananda, Karunasena, & Pearson, 2023). Furthermore, another study in Romania found that the accessibility for food recovery or redistribution played a role in household food waste (Archip, Banatean-Dunea, Petrescu, & Petrescu-Mag, 2023).

2.5. Theoretical Frameworks of Food Waste Research

2.5.1. Theory of Planned Behavior

The theory of planned behavior (TPB) model ascertains that "intentions to perform behaviors can be predicted with high accuracy from attitudes toward the behavior, subjective norms, and perceived behavioral control; and these intentions alongside perceptions of behavioral control, account for considerable variance in actual behavior" (Ajzen, 1991). A range of studies have focused on the use of the TPB in order to determine predicted intention to reduce food waste and food waste behavior such as the intent to waste food was higher when they perceived that people around them also did (Aktas et al., 2018; Attiq, Danish Habib, Kaur, Junaid Shahid Hasni, & Dhir, 2021; Broshuis, 2021; Mondéjar-Jiménez, Ferrari, Secondi, & Principato, 2016; Stancu, Haugaard, & Lähteenmäki, 2016).

Other studies found that perceived social benefits increased motivation to reduce food waste behaviors (Chengqin et al., 2022; Ribbers, De Pelsmacker Geuens, Pandelaere, & van Herpen, 2022; Visschers, Wickli, & Siegrist, 2016; Wang, Li, Li, & Chen, 2022). Although, one study in Croatia found that participants reported feeling guilty about wasting food but continued to do so because they had no perceived social benefits from changing their habits (Ilakovac, Cerjak, & Voca, 2020). Previous literature also found that minimizing food waste was positively associated with a sense of environmental concern (Chengqin et al., 2022; Abdelradi, 2018). In Guelph, Canada, households that had perceived guilt from wasting food were less likely to waste food than those who did not have perceived guilt, additionally, households that had social motivation to reduce their environmental impact were also less likely to waste food (Parizeau, von Massow, & Martin, 2015).

2.5.2. Stimulus Organism Response Theory

Stimulus Organism Response Theory posits "that multiple internal or external elements in the environment act as stimuli (S) driving the internal organismic state of an individual or organism (O), which drives individual responses (R) to the stimuli" (Talwar, Kaur, Kumar, Salo, & Dhir, 2022). For reference to food waste behavior and awareness research, the stimuli usually correspond to internal or external elements that influence an individual's (O) thoughts or perceptions that cause responses such as minimizing or increasing their food waste.

A study measuring food waste behavior used the SOR theory through conceptualizing moral norms and anticipated pride (S), intentions against food waste (O), and the use of leftover food and over-purchasing food as a response (R). It concluded that participants who felt a sense of guilt and regret increased their intentions to avoid wasting food, and their sense of pride increased when they diminished their household food waste (Talwar, Kaur, Kumar, Salo, & Dhir, 2022). Another study used dining out and planning meals as stimuli, the intentions to do one or the other as O, and the attitude towards taking away leftovers, the behavior of taking a takeaway box, and eating the leftovers as responses. Their findings indicated that participants who plan their meals in advance are more likely to eat their leftovers and avoid wasting food, and furthermore, participants who order more dishes than needed or order too much whilst dining out are motivated to take leftovers away to guilt-off setting rationalization but not that they necessarily eat them afterward (Talwar, Kaur, Okumus, Ahmed, & Dhir, 2021).

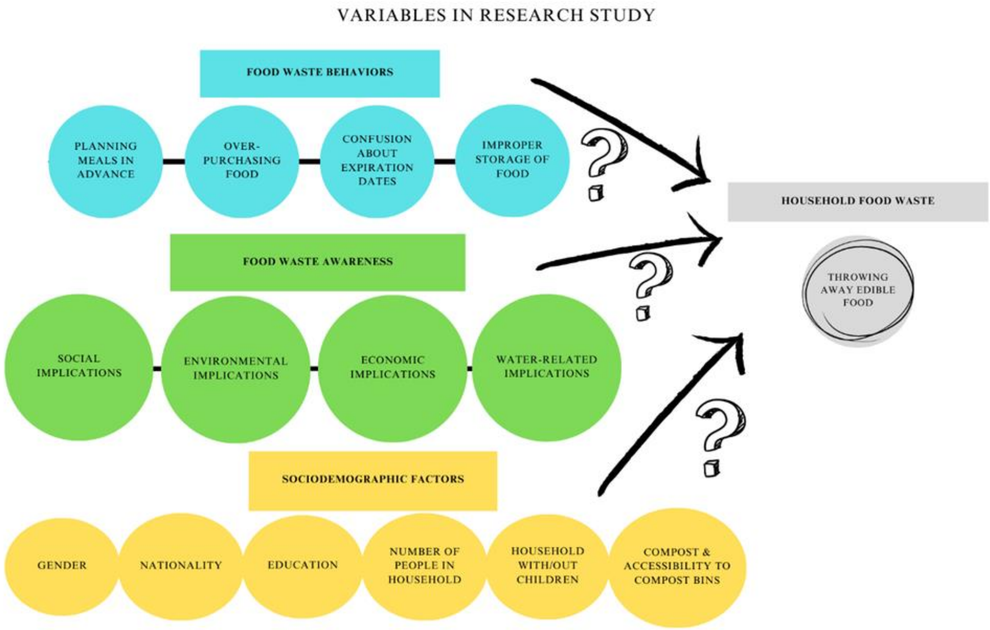
SOR theory as a method of studying consumer behavior has been increasingly growing in popularity due to its adaptability to incorporate multiple variables to serve as stimuli, influencing both cognitive and emotional processes. It also accommodates both positive and negative responses, which allows for a more comprehensive view of people's insights into a topic. Furthermore, it incorporates not only social perception such as TPB but also a representation of both internal processes and external actions which impact consumer decision-making.

2.6. Conceptual Framework

The diagram below shows all the variables in the study and their expected relationships (*See Figure 1*). *Throwing away edible food* is the main dependent variable in this study and will equate to household food waste. As per previous studies, some food waste behaviors that increase or decrease household food waste include planning meals in advance, over-purchasing food, confusion about expiration dates and storing food improperly.

The literature review indicates that there is a wide range of implications that arise from household food waste, which are the sustainability pillars: social, environmental, economic, with an additional pillar that considers water-related waste. By separating the implications of food waste into these four pillars, it can be determined later if the awareness of any *one* (or all) pillars can increase or decrease household food waste.

Figure 1. Expected Relationships between Variables



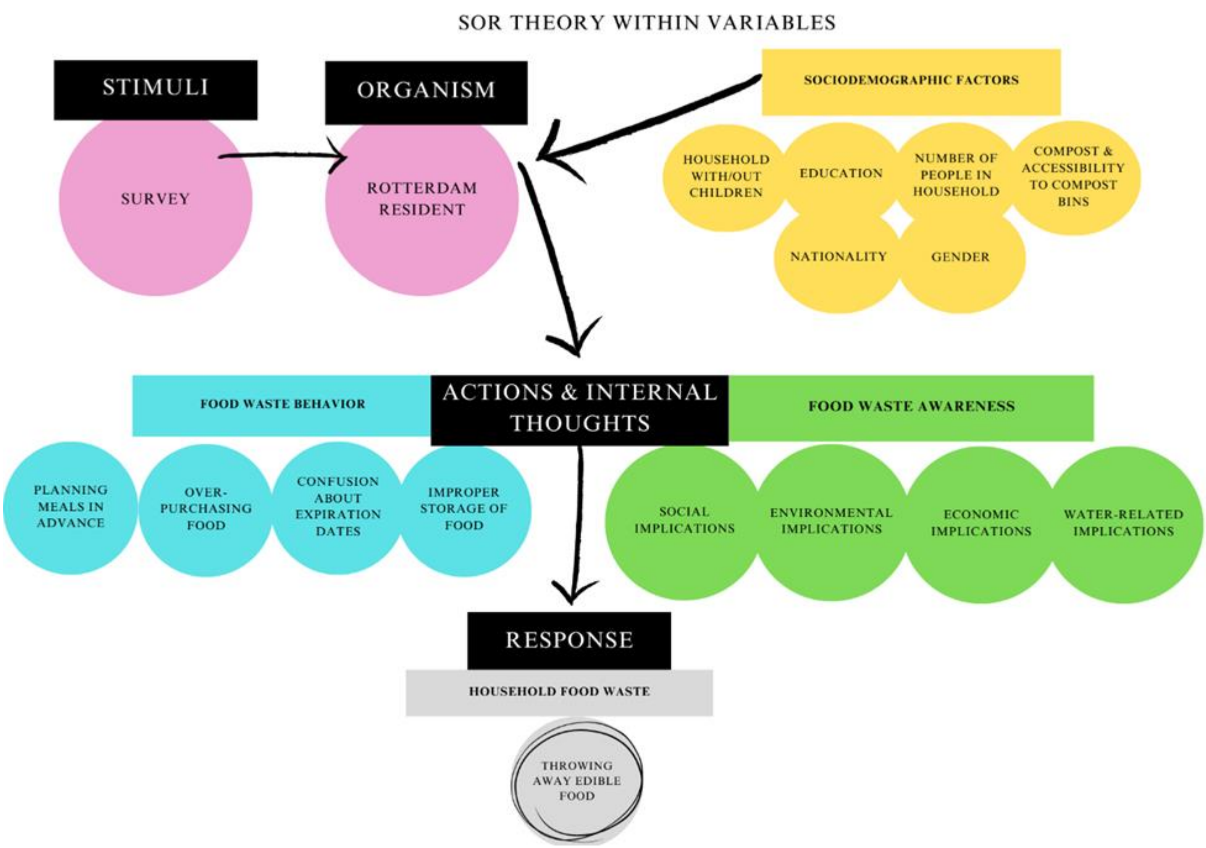
The research model in this study measures awareness through a specific lens. The dimensions of awareness can vary depending on the specific meaning given to awareness. Awareness, as understanding, can reflect an individual's conscious recognition of the given pillar (Timmermans & Cleeremans, 2015). Awareness can equate to how *important* the given pillar is to the individual and therefore their understanding of the topic. Awareness can also equate to *knowledge*, in other terms, the "greater the awareness on", the greater the *knowledge* on the respective pillar (Gafoor, 2012). The *intent to change* their behavior can also be a component of awareness as it encompasses not only knowledge and understanding but also the motivation to take action based on that awareness.

As shown through previous studies, when individuals become aware of the implications of food waste, it is more likely that their food waste diminishes. Due to time constrictions in this study, instead of measuring levels of awareness before and after a specific awareness intervention, the researcher decided to encompass these components of awareness (perceived importance, knowledge, and intent to change) to measure food waste awareness (social, environmental, economic, and water-related).

The study collects sociodemographic data to determine if there is a relationship between these factors and household food waste. As per the literature review, demographic factors can determine if an individual has increased or decreased food waste, and therefore age group, gender, nationality, and level of education. Highly relevant is the household composition, namely the number of people per household and if there are children present. Finally, there is the accessibility to compost bins.

The SOR Theory is used in this study as demonstrated in the conceptual framework below (*See Figure 2*). A common assumption of SOR theory is that a consumer's emotions will influence, as an important criterion, the response that the consumer has to the exposed environmental stimulus (Adrin Hetharie, Surachman, Hussein, & Puspaningrum, 2019). The environmental stimulus used in this study is the survey itself asking the respondent's questions about their food waste. The organism in this study is the respondent. Sociodemographic factors make up the respondent and could potentially influence their self-reported household food waste (response). The aim of asking the respondents about their food waste awareness and food waste behaviors is to uncover their actions and internal thoughts. By proxy, uncovering whether any of the predictors influence the respondent's food waste (response).

Figure 2. Conceptual Framework



3. Chapter 3: Methodology

This chapter outlines the research design and methodology used in this study. It presents the strategy before displaying in an operationalization table the variables described in the aforementioned conceptual framework. There will be a section describing the data collection as well evaluating the reliability and validity. Finally, a summary for the chosen data analysis methods.

3.1. Research Strategy

This study conducted a survey as its primary research strategy. The use of primary data collection, specifically the survey method, was chosen due to its capacity to obtain information from large samples of the population in a timely and efficient manner. Survey research identifies both an independent and dependent variable, however, the researcher cannot explicitly control the variables (Glasow, 2005). Based on an extensive literature review, the researcher has gathered hypotheses to test against these variables. In doing so, the hypotheses can then be tested against observations and make an estimation for the population.

The survey administered for this research contains close-ended questions in the form of multiple-choice and the Likert scale to increase accessibility for the respondents. Survey questions must use wording that is consistent with the educational level of the intended respondents to prevent confusion and implement clarity (Glasow, 2005). Within the scope of this research study, the respondents were middle-class residents of Rotterdam, rendering the chosen terminology suitable for this population. Furthermore, the terminology was appropriate in both English and Dutch, with respondents given access to both languages. The survey design is appropriate for the research objectives and questions because it aims to ascertain the data on household food waste in a concise form of reaching the intended population.

3.2. Operationalization

The Operalization of this research was designed on previous studies regarding household food waste and its primary indicators. The indicators for awareness were created based on the Stimuli Organism Response Theory. The following operationalization table demonstrates the theories, variables, and scale of measurement used in this study based on the main indicators.

Table 1. Operationalization Table

Research Variables	**Theory/Concept**	**Scale of Measurement**
Household Food Waste (Dependent)		
Throwing Away Edible Food	Throwing Away Edible Food is the main dependent variable measuring household food waste. This variable is representative of the response in the SOR Theory.	The scale of measurement regarding throwing away edible food was the Likert Scale. It is measured by "how often do you throw away edible food per week?". The scale only indicated that "1 = Never" and "5 = Always".
Food Waste Behaviors (Independent)		
Over-purchasing Food Confusion about Expiration Dates Storing Food Improperly Planning Meals in Advance	These behaviors were chosen due to previous studies that have suggested an increase or decrease in food waste. Regarding SOR theory, these variables represent the organism (respondents) actions.	The scale of measurement for food waste behaviors was the Likert Scale. It is measured "how often do you perform given behavior per week?". The scale only indicated that "1 = Never" and "5 = Always".
Food Waste Awareness (Independent)		
Perceived Importance of <u>Social</u> Implications Knowledge of <u>Social</u> Implications Intent to Change Behavior to Improve <u>Social</u> Implications Perceived Importance of <u>Environmental</u> Implications Knowledge of <u>Environmental</u> Implications Intent to Change Behavior to Improve <u>Environmental</u> Implications	The three components of awareness here are perceived importance, knowledge, and intent to change. They are divided into the four implications found in the literature review of food waste: social, environmental, economic, and water related. Regarding SOR theory, these variables represent the internal thoughts of the organism (respondent).	The scale of measurement for awareness was the Likert Scale. Perceived importance was measured by "how often do you think about given implication per week?". The scale only indicated that "1= Never" and "5 = Always. Knowledge was measured by "how much do you know about given implication per week?". The scale only indicated that "1 = a little" and that "5 = a lot". Intent to change behavior was measured by "how likely are you to reduce your food waste to improve given implication?". The scale only indicated that "1= Very unlikely" and that "5 = Very likely".

Perceived Importance of <u>Economic</u> Implications Knowledge of <u>Economic</u> Implications Intent to Change Behavior to Improve <u>Economic</u> Implications Perceived Importance of <u>Water-Related</u> Implications Knowledge of <u>Water-Related</u> Implications Intent to Change Behavior to Improve <u>Water-Related</u> Implications		
Sociodemographic Factors (Independent)		
Gender Nationality Education Age Group Number of Household Members Household With or Without Children Accessibility of Composting	Based on previous literature, these sociodemographic factors have been proven to influence food waste behaviors, and therefore will be used in this study to find further explanation in relationships. Regarding SOR theory, they are characteristics of the organism (respondent).	The scale of measurement for sociodemographic factors was multiple choice. For gender, the options either "female", "male", or "prefer not to say". For nationality, the options were "Dutch", "other European citizen", and "non-European". For education, the options were "high school diploma or lower", "university diploma", or "master's diploma or higher". For age, the options were "20-29", "30-39". "40-49". "50-59". "60-69", or "70 and above". For number of household members, the options were "1", "2", "3", or "4 or more". For households with or without children, the options were "yes" or "no". For accessibility of composting, the options were "yes" or "no".

3.3. Data Collection Method

3.3.1. Sample Size and Selection

The purpose of this research is to determine the influence of the independent variables on the dependent variable. Considering the time and budget limitations, a simple random sampling method was used. The collection of data came from the residents of Struisenberg. Struisenberg, as of February 2023, had a population of 5,755 residents (CBS, 2023). For the feasibility of the data collection, the sample size was 361, 10% of the population. The calculation was made based on a 5% margin of error, a confidence level of 95%, and a sample proportion of 50%. Data collection for the 361 respondents spanned from 05/05/2023 to 20/06/2023. The researcher did not put a time stamp on the data collection to fulfil the precise sample size and to maintain validity for the results. For confidentiality purposes, the researcher did not collect any personal information about the respondents, i.e., names, addresses, phone numbers, or emails. An Ethics Statement was produced in the research proposal. The research process was accepted through the Education Management Office at the Institute for Housing and Urban Development Studies via a fieldwork/data collection letter before any data collection was conducted.

3.3.2. Survey Specifics

The survey constructed for this research was made under Google Forms and maintained an option for the languages with the most significant linguistic presence in Rotterdam: English and Dutch. The survey itself consisted of 8 questions measuring sociodemographic factors, 5 questions measuring food waste behavior, and 12 questions measuring the awareness of food waste implications. The research required a sample size of 361 participants, to complete this objective, it was important that the survey was accessible and straightforward.

For data collection, the researcher performed door-to-door and face-to-face outreach. Given the limited timeframe of the research, the researcher created a flyer with a QR code linking to the survey and distributed the flyer throughout the neighborhood (*See Figure 3*).

Figure 3. Survey Flyer

3.4. Data Reliability and Validity

Reliability in quantitative research refers to the precision of an instrument to repeatedly measure the principle (Heale & Twycross, 2015). This means that if the instrument (survey) used to measure gave the same results on repeated occasions, ceteris paribus, the results would be reliable. Reliability was considered when designing the sample size and selection process, described previously.

Validity in quantitative research refers to the accuracy of the instrument used to measure the principle (Heale & Twycross, 2015). In other words, validity quantifies the extent to which the measurement (results of the survey) is representative of the principles intent to measure (design of the survey). The validity was considered in the design of the questions as described, informed by prior research and the simplicity of the language chosen. The bilingual options were thrice checked by native language bilingual speakers to consider linguistic and cultural implications of wording.

Despite these careful considerations in the design of the research methodology, the researcher must still consider the inevitable diverging perspectives, such as inherent biases, on the intended-received message discrepancy from each question. Furthermore, considering the SOR theory, the research has no control whether or if respondents attempted to misreport their behavior consciously or unconsciously, due to poor recollection or self-correcting biases. Moreso, given the digital form and data collected mechanism, it is possible that respondents could have participated beyond the geographical scope of Struisenberg neighborhood. As such, these and other possibilities are included in a limitation section offered in the Conclusion Chapter.

3.5. Data Analysis Methods

3.5.1. Quantitative Analysis

Quantitative analysis is widely applied across the social sciences. It relies on statistical, mathematical, or numerical primary or secondary data analysis (Smith, 2015). Quantitative research describes answering questions related to measurement, relations, and or casual effects. In quantitative research, the researcher must describe and test relationships and/or examine cause-effect relationships. Findings of quantitative research can be generalized to a given population if the sample is based on random sampling and large enough. Random sampling of each member of the population has an equal chance of being included in the sample; while the larger the sample, the lower the chance of getting a lopsided sample. Standardized approaches of quantitative research permit the study to be replicated (Smith, 2015).

3.5.2. Descriptive and Inferential Statistics

Descriptive statistics is the process of describing, graphing, or summarizing data of a sample in a meaningful way to identify patterns that emerge from the data (Smith, 2015). Inferential statistics use data from a sample to make inferences about the larger population and predict values (Smith, 2015). This research presents graphs of the data collected to show recurring themes and patterns. The research also uses correlation and multiple regression analysis to generalize about the population from which the sample data was collected. This research used the program STATA and Microsoft Excel to perform statistical analysis and visualizations of the data.

3.5.3. Correlation Analysis

Correlation analysis in statistical research is used to measure the strength of the linear relationship between two variables: x and y. For this research, each of the independent variables was correlated to the dependent variable, household food waste. Correlation analysis is used to calculate the level of change in one variable, household food waste, due to the change in the other predictors. Correlation analysis is usually interpreted from a scale of -1.0 to 1.0, indicating a perfect negative or positive correlation between two variables, while 0.0 represents no association, respectively (Smith, 2015). The closer the absolute value is to 1, the stronger the correlation (*See Table 2*).

Table 2. Range of Strength in Correlation Coefficients

Correlation Coefficients	**Strength**
0.0 to 0.2	*Very weak*
0.2 to 0.3	*Weak*
0.3 to 0.4	*Moderate to Weak*
0.4 to 0.6	*Moderate*
0.6 to 0.7	*Moderate to Strong*
0.7 to 0.8	*Strong*
0.8 to 1.0	*Very Strong*

While a significant relationship may be identified by correlation analysis, it is important to note that correlation does not imply causation, thus the cause cannot solely be determined by the analysis (Ceravolo, Coletta, Miraglia, & Palma, 2021). A significant relationship between the two variables implies that there is more to understand about the relationship and that there are underlying factors that should be explored further to understand the cause.

3.5.4. Multiple Regression Analysis

Multiple regression analysis seeks to uncover the relationship between a single dependent variable, and several independent variables. The purpose of multiple regression is to measure the impacts of a combination of independent (or explanatory) variables on a dependent variable (household food waste) (Smith, 2015).

There are two kinds of regression: linear and nonlinear. In multilinear regression, the model assumes a linear combination of the independent variables to predict the dependent variable. While for nonlinear regression, the model does not need to assume a linear combination and therefore it can take more complex functional forms. The key difference between the two is the assumption of linearity. For this study, the use of multilinear regression was used. The researcher chose to do so because multilinear regression models have simpler structures, since they are assumed to be linear, the interpretation of the coefficients is more straightforward. Furthermore, nonlinear regression is prone to overfitting since it can take on more complex functional forms and be sensitive to initial values over the remaining values. Overfitting is a problem that occurs when the statistical model is too complex and begins to describe the random error in the data rather than the relationships between variables (Frost, 2017).

4. Chapter 4: Results, Analysis, and Discussion

This chapter describes the results of the survey and respective analyses of the data collected. First, there is the descriptive and inferential statistics. Then there is an interpretation of the correlation analysis. Finally, there is the multilinear regression analysis. Throughout the chapter, the researcher includes a discussion on the findings.

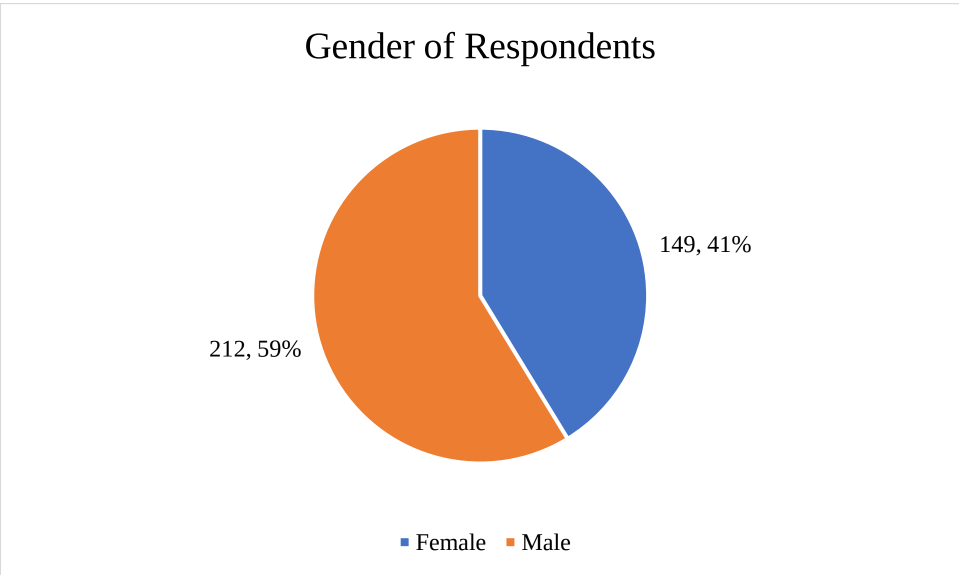
4.1. Descriptive and Inferential Statistics

The data collected in the survey was both quantitative and nominal. The data collected via the Likert Scale was quantitative (household food waste, food waste behavior, awareness). However, the data for sociodemographic factors had to be converted from nominal values into numerical values.

4.1.1. Descriptive Statistics of Sociodemographic

Out of the 361 respondents, 149 (41%) were *female*, and 212 (59%) were *male* (*See Figure 4*). While there were more male respondents than females, the researcher believes the data continues to be representative of the residents of Struisenberg because as of 2023, there are 3,005 women and 2,745 men living in the neighborhood (CBS, 2023).

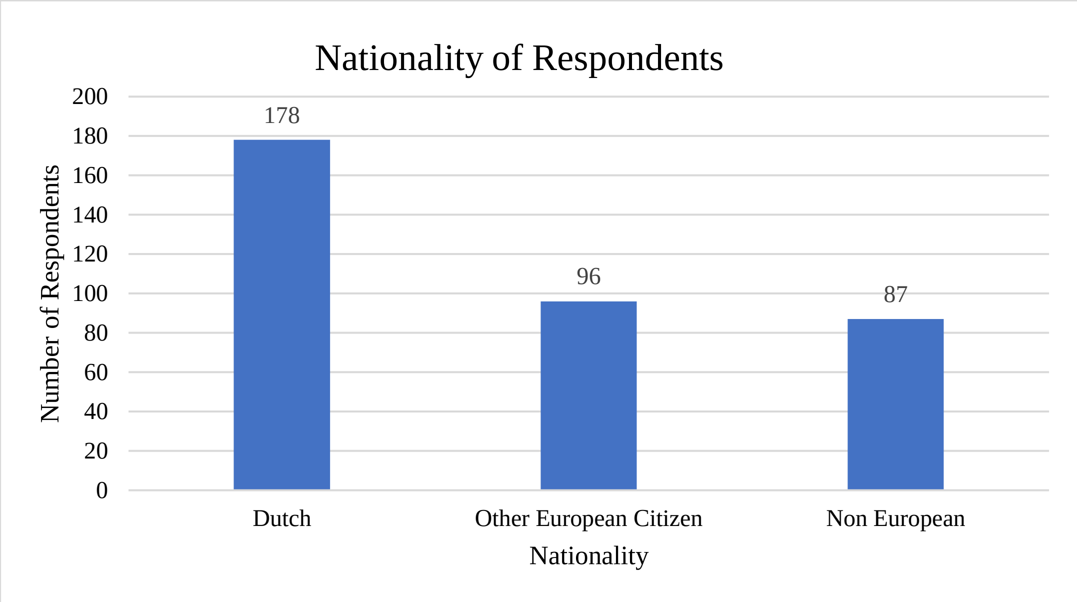
Figure 4. Gender of Respondents Pie Chart



The nationality of the respondents was divided into Dutch, Other European Citizens, and Non-European for the expediency of using the data on the Stata programming. The Dutch make up the majority at 178 respondents, then 96 other European citizens, and finally 87 non-European citizens (*See Figure 5*). Although there is no census data on the nationality of the residents of

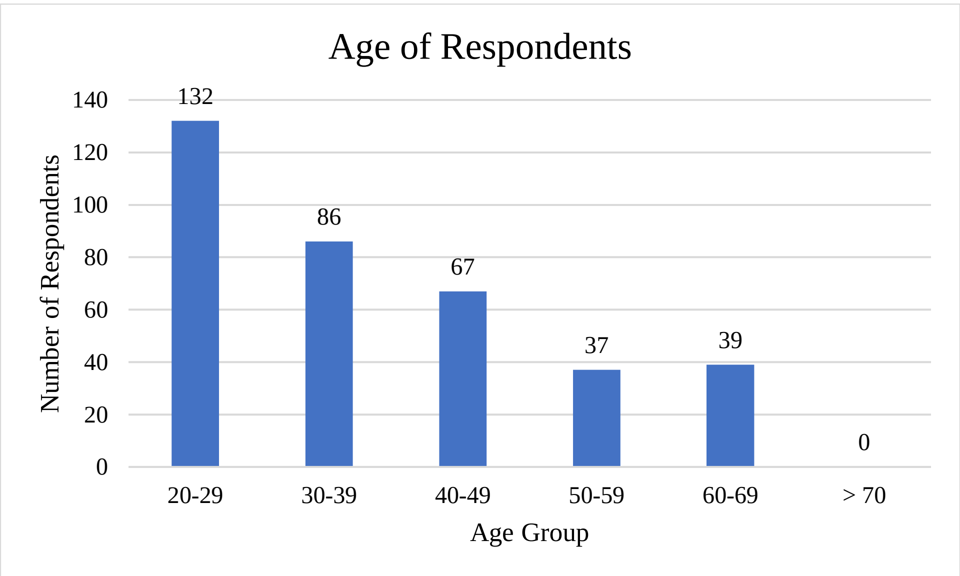
Stuisenberg, the researcher posits that this sample adequately represents the population given that Rotterdam is an international city.

Figure 5. Nationality of Respondents Bar Graph



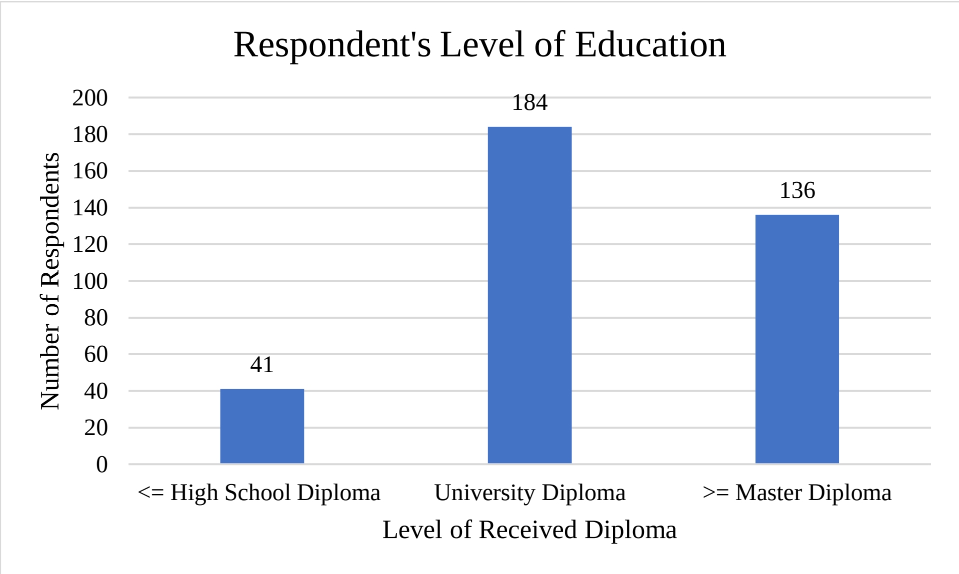
The respondent's ages were grouped into intervals of ten, such as 20-29,30-39, and subsequent ranges until 70 or above (*See Figure 6*). The data collection failed to collect anyone over the age of 69. The researcher suggests this occurred because of the age of the researcher, as older respondents exhibited reluctance in participating in door-to-door or face-to-face interactions. Furthermore, most respondents were aged 20-29 or 30-39, which corresponds to census data of the neighborhood wherein 37% of the population are 15-25 years old and 33% are 25-45 years old (CBS, 2023).

Figure 6. Age Group of Respondents Bar Graph



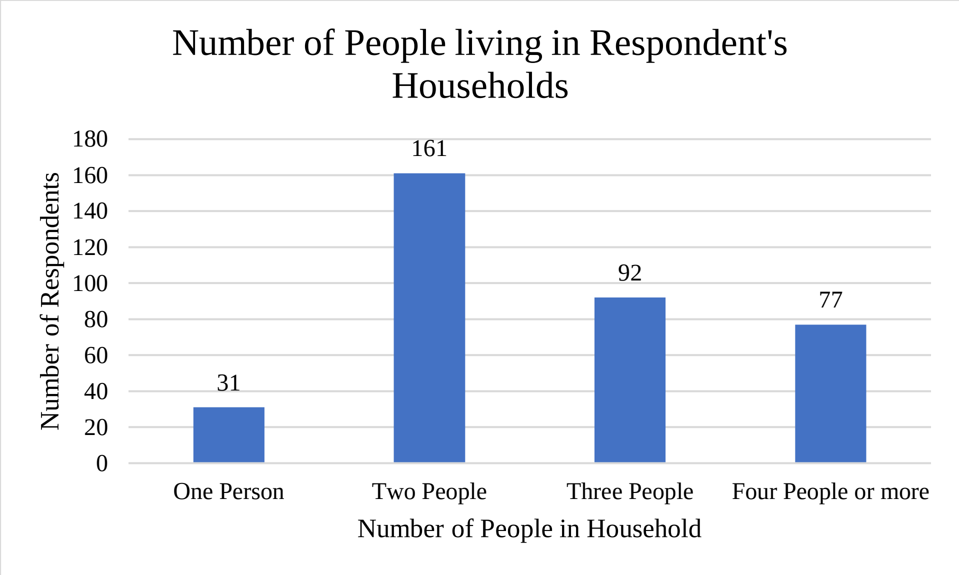
The respondent’s level of education was also measured as a high school diploma or lower, a university diploma, or a master’s diploma or higher. The results demonstrated that most respondents were highly educated with either a university diploma (184) or a master’s diploma or higher (136), with only 41 respondents holding a high school diploma or lower (*See Figure 7*). The researcher believes this to be in accordance with the educational character of the population because generally in middle to high class neighborhoods, the individuals usually have higher levels of education.

Figure 7. Respondent's Level of Education Bar Graph



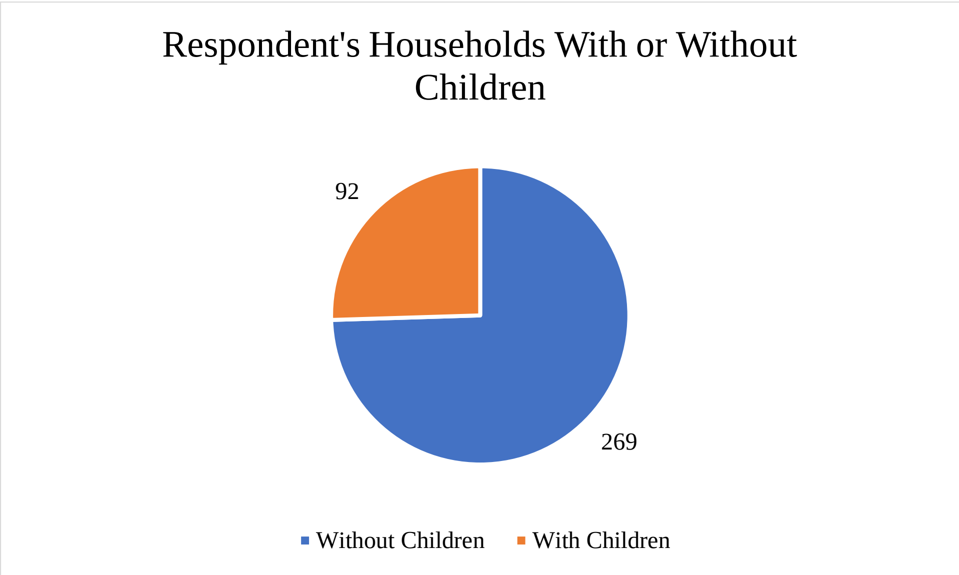
In terms of personal household demographics, this study assessed the number of individuals residing in the respondent’s household (*See Figures 8*). The researcher suggests that the distribution of household numbers in the sample aligns with the overall trend, given that a significant proportion of respondents reported living in two-person households. Since most respondents were in their twenties or thirties, this age group is likely to be more representative of individuals residing in smaller households. Furthermore, only 31 respondents reported living alone, which aligns with the housing crisis and rent prices in Rotterdam.

Figure 8. Number of people in Respondent's Households Bar Graph



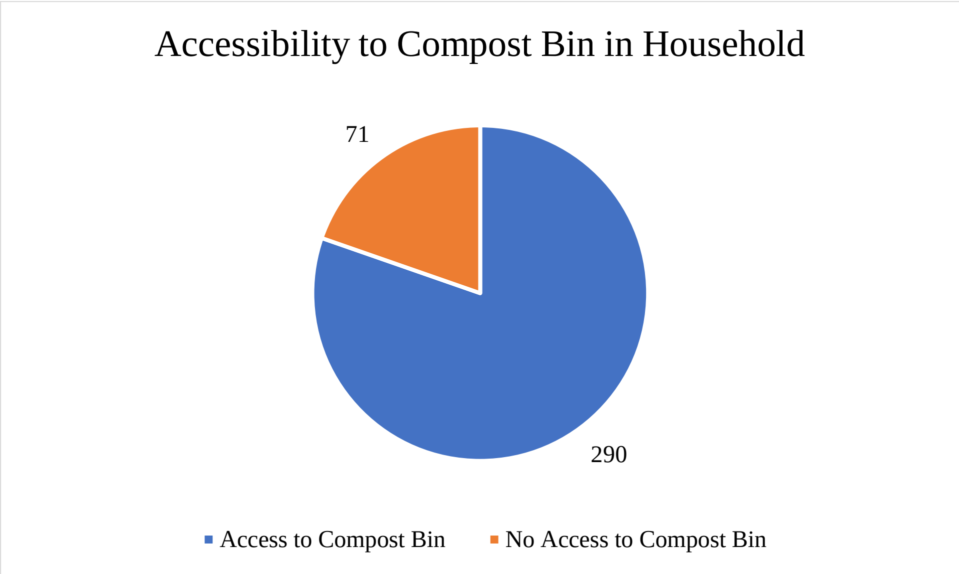
The researcher observes that the distribution of households with or without children corresponds to the data, given that a significant number of respondents reported living without *children* (269) (*See Figure 9)*. These results correspond with the sample given that the prevalence of respondents in their twenties or thirties may not have children. It is also useful to note that the survey did not specify the age of children, only that the survey may only be completed by someone over the age of 20, this may have influenced the responses.

Figure 9. Respondent's Households with/out Children Pie Chart



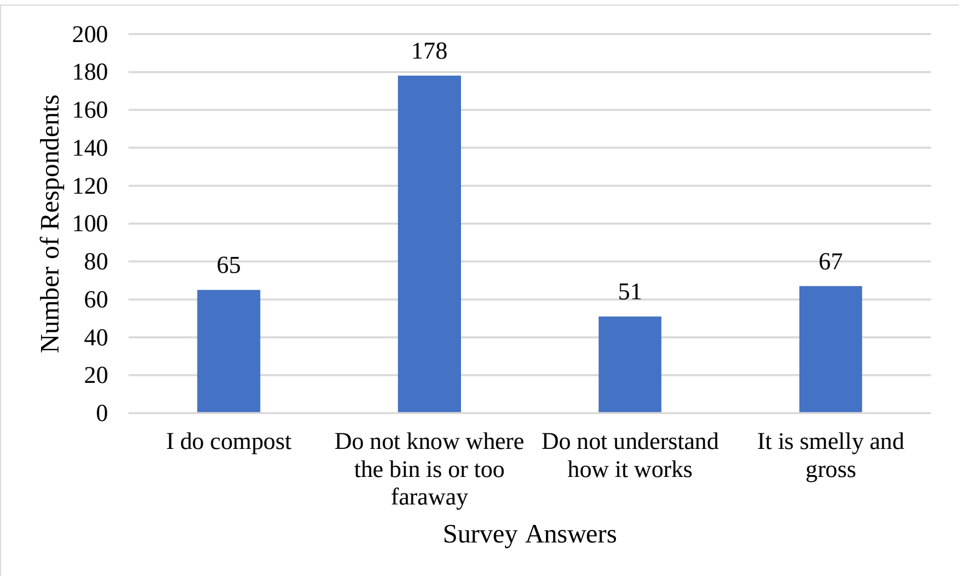
The last demographic collected for this study contained the topic of composting. The survey asked respondents whether they had access to a compost bin in their household (apartment complex or house) (*See Figure 10*). The results of the compost questions indicate that a significant proportion of residents in the sample do not have access to a compost bin (290). This observation aligns with the broader compost statistics in Rotterdam, given that the municipality has minimized the number of compost bins available throughout the city.

Figure 10. Accessibility to Compost Bin in Respondent's Households Pie Chart



Furthermore, if the respondent does not compost, why not in the form of four answers: "I do compost", "Do not know where the bin is or too far away", "Do not understand how it works", and "It is smelly and gross" (*See Figure 11).* The primary reason reported by respondents for not composting is the lack of access to a compost bin (178). Furthermore, it can be logically inferred that out of the 71 respondents who have access to a compost bin, 65 of them reported composting. This means that most residents who have access to a compost bin are utilizing it.

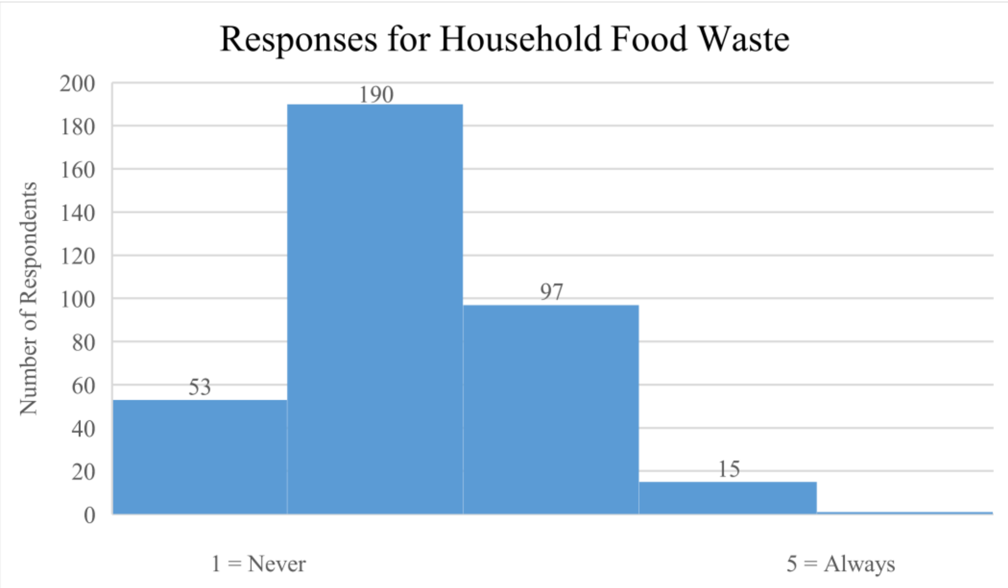
Figure 11. Reasons for Not Composting Bar Graph



4.1.2. Descriptive Statistics of Household Food Waste

The dependent variable in this study is Household Food Waste, it was measured by asking respondents' how often they throw away edible food. The results of this self-reported data is shown in the Histogram below (*See Figure 12*). The distribution of responses is heavily skewed towards the left, thereby indicating that the majority of respondents reported throwing away edible food closer to the "never" category. Approximately 97 respondents reported towards the middle of the spectrum. Meanwhile, only 15 respondents answered closer to the higher end of the spectrum. Crucially, no respondent answered the most right answer, 5, i.e., "always". However, current statistics on Rotterdam household food waste suggest that this number should be much higher. Thus, it may be that respondents do not actually waste as much food as these macro-statistics suggest, and therefore this data may not be a good representation of the population. Another option is that the respondents did not accurately report how often they throw away edible food, this may be a limitation of self-reported data, which will be further discussed in the limitations section.

Figure 12. Responses for Household Food Waste Histogram

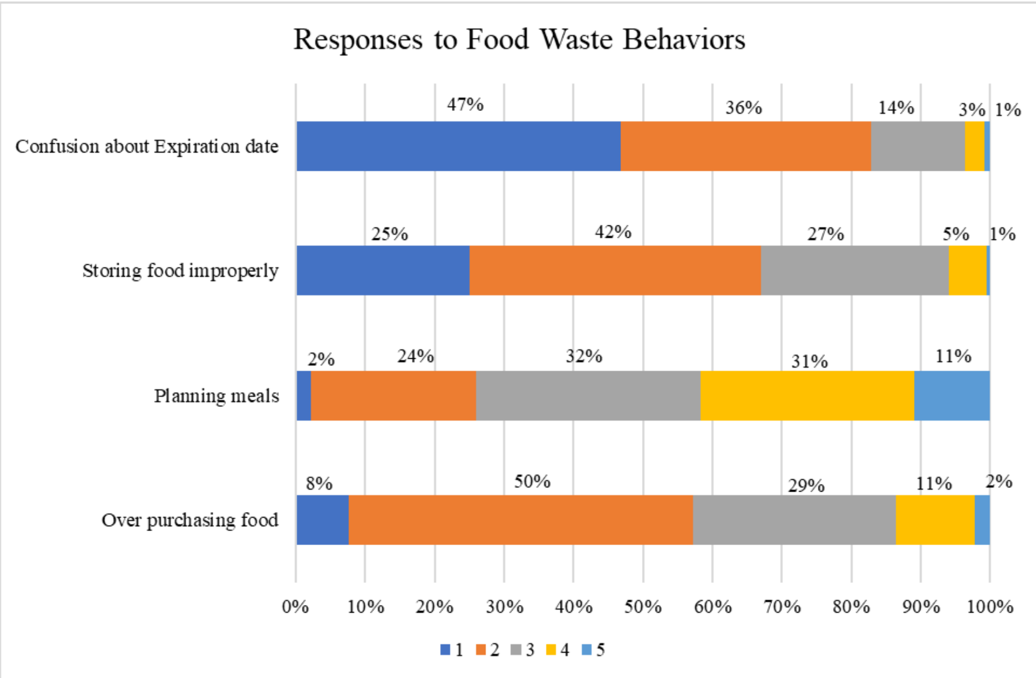


4.1.3. Descriptive Statistics for Food Waste Behavior

To visualize the food waste behaviors reported by the respondents, a 100% stacked bar graph was chosen by the researcher (*See Figure 13*). As mentioned in the Operalization table, the survey utilized the Likert Scale, however it was portrayed as a scale where 1 represented "Never" and 5 represented "Always". When the respondents were asked about the frequency of their behaviors per week, they had to select a value within this scale, not any specific option.

As can be seen from the graph, a majority of respondents indicated that they performed the behaviors “confusion about expiration dates”, “storing food improperly”, and “over-purchasing food” closer to never. Notably, 47% of the respondents reported rarely experiencing confusion about expiration dates and having to throw away edible food (household food waste). Similarly, 42% of the respondents reported rarely storing food improperly and having to throw away edible food, while 50% also reported that they are almost never over-purchase food during grocery shopping. On the other hand, for planning meals in advance, roughly 60% of the respondents answered within the middle or the higher end of the spectrum, closer to always. This suggests that the majority of respondents engage in meal planning to some extent.

Figure 13. Responses of Food Waste Behaviors Stacked Bar



Previous literature suggests a positive correlation between these behaviors and the amount of food waste generated per household. Furthermore, considering Rotterdam’s statistics that indicate very high amounts of household food waste, the respondent’s answers seem inconsistent. Additionally, very few of the respondents reported their behaviors on the higher end of the spectrum (closer to “always”). Thus, it may be that respondent’s food waste is not influenced heavily by these food waste behaviors, or that the residents do not waste as much food as current reporting suggests.

Table 3. Descriptive Statistics of Food Waste Behaviors

	Over Purchasing Food	Planning Meals in Advance	Storing Food Improperly	Confusion about Expiration Dates
Mean	2.51	3.25	2.14	1.75
Median	2	3	2	2
Mode	2	3	2	1
Standard Deviation	0.87	1.01	0.88	0.85
Skewness	0.65	0.01	0.40	1.11

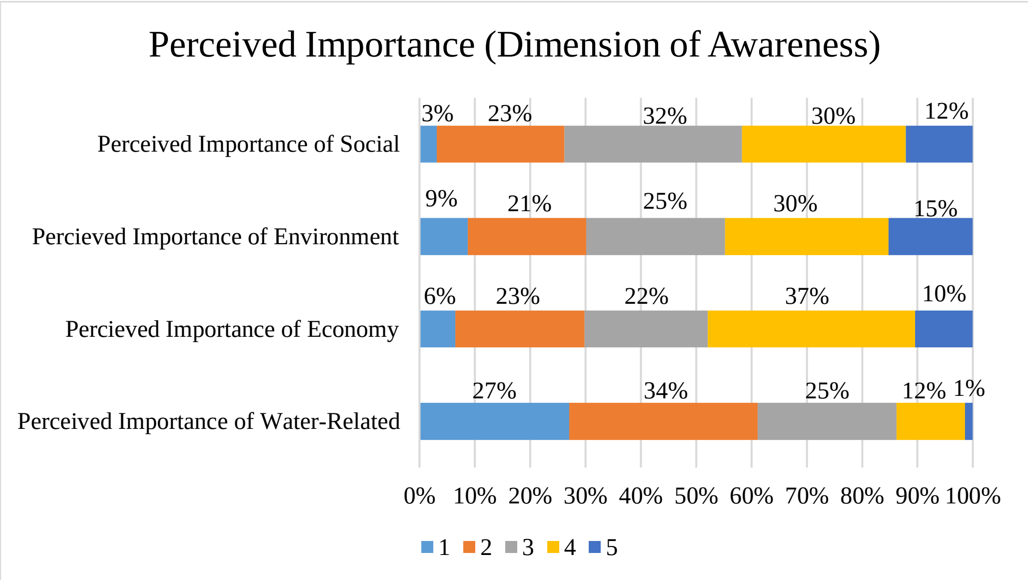
The mean for the over-purchasing food, 2.51, and storing food improperly, 2.14, indicated that, on average, respondents reported a moderate level of over-purchasing food and storing food improperly. While for planning meals in advance, the respondents perform this behavior slightly higher than the average. The lowest mean is confusion about expiration dates, indicating that the respondents perform this behavior on average, the least. The median for planning meals in advance indicates that roughly half of the respondents reported planning meals in advance occasionally, while the other reported doing so less frequently. For the other behaviors, the median was lower at 2, meaning that the respondents reported performing these behaviors on the lower spectrum. The results for mode indicate that respondents reported on the lower spectrum, especially for confusion about expiration dates, and only at the middle of the spectrum for planning meals in advance. The only standard deviation value that has greater variability is for planning meals in advance at 1.01, the remaining behaviors indicate that respondents were consistent in their answers. The skewness values all indicate a right skewness in behaviors. The value for over purchasing food (0.65), indicating that the distribution is skewed towards higher levels of over purchasing food at the groceries stores by respondents. While the skewness value for confusion about expiration dates (1.11) indicates that the distribution is highly concentrated towards lower levels of confusion about expiration dates.

4.1.4. Descriptive Statistics for Food Waste Awareness

To visualize the responses for food waste awareness, the researcher developed 3 different 100% stacked bar graphs. The survey questions for awareness were phrased similarly for each dimension of awareness as opposed to the pillars (social, environmental, economic, water-related). For *perceived importance*, the question was phrased "how often", with the Likert scale ranging from "1 = never", "5 = always". For *knowledge*, the questions were phrased "how much", ranging from "1 = a little", "5 = A lot". For intent to change, the questions were phrased “how likely”, ranging from “1 = very unlikely”, “5 = very likely”. Therefore, the researcher decided to present the results via dimension, and not pillar.

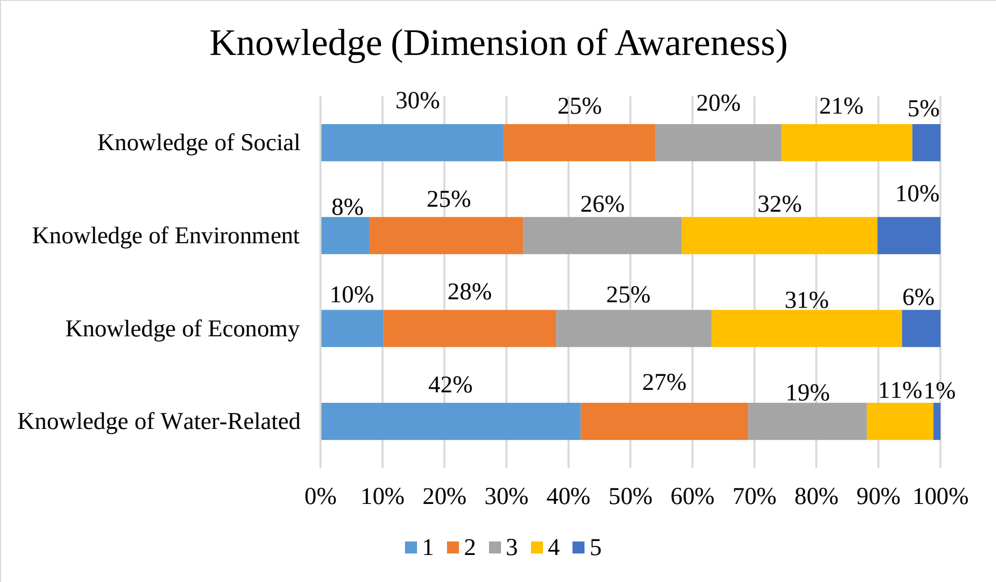
The results indicated that respondents reported giving the most perceived importance to environmental implications, with about 15% of the respondents reporting on the highest end of the spectrum (*See Figure 14*). While for perceived importance for social implications, the majority of the respondents reported the middle to high end of spectrum. For perceived importance of economic implications, the majority at 37% reported putting high importance on economic implications. However, for water-related implications, the majority of the respondents reported on the lower end of the spectrum, with only 1% reporting high perceived importance.

Figure 14. Perceived Importance Responses Stacked Bar



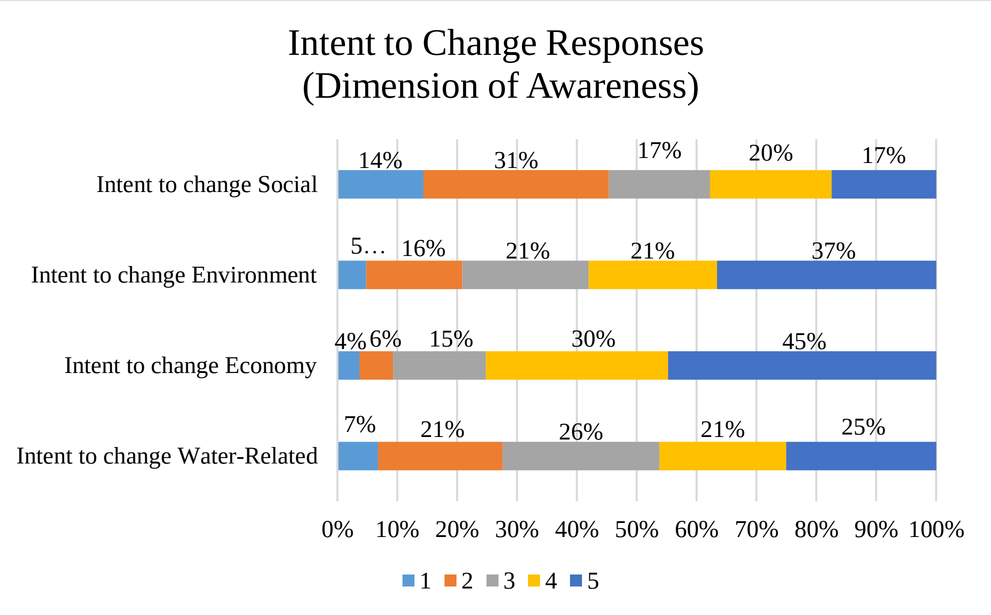
The results for knowledge of social implications indicated that the majority of respondents reported on the lower to middle spectrum or knowing a moderate amount about the social implications (*See Figure 15*). While the majority of respondents reported knowing more about environmental implications, the most respondents recording at the highest end of the spectrum (a lot). Similarly, the majority of respondents reported having higher knowledge on economic implications. However, for water-related implications, the majority at 47% reported on the lowest end of spectrum (a little) or knowing the least.

Figure 15. Knowledge Responses Stacked Bar



The results for intent to change behavior to improve implications is shown in the stacked bar below (*See Figure 16*). The results indicate that the majority of respondents reported on the lower spectrum for intent to change behavior to improve social implications. While the majority of respondents reported on the higher spectrum with 37% having a higher intent to change their behavior to improve environmental implications. The most consistent result is that the majority of respondents reported on the highest spectrum to improve economic implications, this however, could be a limitation of the phrasing "how likely are you to reduce your food waste to *save* money?". The majority of respondents regardless of their knowledge or perceived importance of economic implications would most likely want to save money and be willing to reduce their food waste to do so. Finally, the results for water-related implications indicate that the respondents answered at every spectrum equally (20-25%)

Figure 16. Intent to Change Responses Stacked Bar



On average, the respondents tended to respond moderately to social awareness as can be seen from the mean values (2.95, 3.25,2.46) in the table below (*See Table 4*). The mode indicates that for perceived importance and intent to change the respondents mostly answered in the higher spectrum, however for knowledge, it was on the lower spectrum (a little). The standard deviations indicate that there was more variability in the answers for intent to change, but all of three were relatively high in variability. The skewness for awareness of social implications indicates symmetrical distributions in the variables as they are all close to zero.

Table 4. Descriptive Statistics of Social Pillar

	Intent to change Social	Perceived Importance of Social	Knowledge of Social
Mean	2.95	3.25	2.46
Median	3	3	2
Mode	2	3	1
Standard Deviation	1.34	1.04	1.24
Skewness	0.16	-0.02	0.30

For the environmental pillar of awareness, the respondents tended to respond on average on the higher spectrum as can be seen by the averages (3.69, 3.21, 3.11) (*See Table 5*). For intent to change behavior to improve environmental implications, the most common answer for the respondents was on the highest spectrum, indicating that the majority are very likely to change their behavior (reduce food waste). The standard deviations indicate high variability in the respondent’s answers. Furthermore, the skewness values are all negative, indicating that the distribution of the data is skewed to the left.

Table 5. Descriptive Statistics of Environmental Pillar

	Intent to change Environment	Perceived Importance of Environment	Knowledge of Environment
Mean	3.69	3.21	3.11
Median	4	3	3
Mode	5	4	4
Standard Deviation	1.25	1.19	1.13
Skewness	-0.49	-0.18	-0.13

For the economic pillar, the respondents on average tended to report on the higher spectrum for intent to change behavior, then in the middle for perceived importance, and on the lower spectrum for knowledge (*See Table 6*). In accordance, the majority of respondents answered on the highest spectrum (very likely) to the intent to change their behavior, this again, could be due to the phrasing of the question. Similarly, the standard deviation values indicate high variability in the data. The table suggests that the data is distributed to the left given that the skewness values are negative.

Table 6. Descriptive Statistics of Economic Pillar

	Intent to change Economy	Perceived Importance of Economy	Knowledge of Economy
Mean	4.07	3.22	2.95
Median	4	3	3
Mode	5	4	4
Standard Deviation	1.08	1.11	1.11
Skewness	-1.13	-0.27	-0.07

For water-related implications, on average, the respondents reported in the middle to high spectrum on intent to change behavior, but lower spectrum for both the perceived importance and knowledge of social implications (*See Table 7*). The respondents reported the least knowledge on water-related implications. Again, the variability in the data is high as the standard deviation values are close to 1. The skewness for intent to change behavior shows that the data is distributed slightly to the left, while for perceived importance and knowledge, it is skewed to the right. This means that there is a higher concentration of responses on the lower spectrum for intent to change behavior, this could be a strong indication that the respondents are the least concerned and know the least about (have the smallest awareness) on water-related implications.

Table 7. Descriptive Statistics of Water-related Pillar

	Intent to change Water-Related	Perceived Importance of Water-Related	Knowledge of Water-Related
Mean	3.37	2.27	2.02
Median	3	2	2
Mode	3	2	1
Standard Deviation	1.25	1.04	1.07
Skewness	-0.16	0.42	0.71

4.2. Correlation Results and Analysis

Correlation analysis was used in this study to indicate the strength and direction of the relationship between the different variables. For readability purposes, the correlation matrices have been highlighted into two colors on a gradient scale: red representing negative correlation and green representing positive correlation. The number presented is the correlation coefficient. The darker each color, the stronger the correlation (*See Table 2*). Further details on statistical significance (p-value) can be found in stated appendices.

4.2.1. Correlation Analysis between Household Food Waste and Food Waste Behaviors

To answer the first sub-question, to what extent do food waste behaviors influence household food waste, the researcher developed a correlation matrix for food waste behaviors and household food waste (*See Figure 17*).

Figure 17. Correlation Matrix of Food Waste Behaviors & Household Food Waste

	Household Food Waste	*Over purchasing food*	*Planning meals*	*Storing food improperly*	*Expiration date*
Household Food Waste	1.0000				
Over purchasing food	0.4257	1.0000			
Planning meals	-0.3691	-0.2312	1.0000		
Storing food improperly	0.5394	0.4097	-0.3123	1.0000	
Expiration date	0.4791	0.2763	-0.1491	0.5248	1.0000

The food waste behaviors used in the above correlation matrix are as follows: over-purchasing food, planning meals (in advance), storing food improperly, and (confusion about) expiration dates. For over-purchasing food, there is a moderate positive correlation at 0.4257. For planning meals in advance, there is a moderate to weak negative correlation of -0.3691. For storing food improperly, there is a moderate positive correlation of 0.5394. Finally, for confusion about expiration dates, there is a moderate positive correlation of 0.4791. All the correlation coefficients are statistically significant at the 95% confidence level (*See Appendix 2*).

This correlation matrix aligns with previous research about food waste behaviors on the grounds that the more people over-purchase food, store food improperly, and are confused about expiration dates, the more household food waste there is. Likewise, the less that people plan their meals in advance, the more food they waste.

The correlation matrix also shows the correlations between each food waste behavior. In this matrix, it is observed that there is a moderate positive correlation between the following:

- Over-purchasing food and storing food improperly: 0.4097.
- Storing food improperly and confusion about expiration dates: 0.5248.

These correlations indicate that the more the respondents over-purchase food, the more likely they are to store food improperly, and the more they store food improperly, the more likely they are to be confused about expiration dates. However, the more they over-purchase food has a weak positive correlation with how likely they are to get confused about expiration dates (0.2763). These observations suggest that there is at-most a moderate correlation between food waste behaviors and household food waste, as well as a moderate correlation between the behaviors themselves. Further analysis is needed to obtain a comprehensive understanding of the data as correlation does not explain causation.

4.2.2. Correlation Analysis between Household Food Waste and Food Waste Awareness

To answer sub-question 2, to what extent does food waste awareness influence household food waste, the researcher created a correlation matrix with 12-independent variables, corresponding to questions on the survey. Each of the four pillars (Social, Environment, Economic, Water-Related) was measured through perceived importance (P.I.), knowledge (K), and intent to change behavior (I.T.C.)(*See Figure 18*). All independent variables had weak or moderate-to-weak correlations, meaning that the more Awareness an individual has, irrespective of pillar or dimension, the less Household Food Waste they claim to produce.

Figure 18. Correlation Matrix of Food Waste Awareness & Household Food Waste

	Household Food Waste	*P.I. Social*	*K. Social*	*I.T.C. Social*	*P.I. Environment*	*K. Environment*	*I.T.C. Environment*	*P.I. Economy*	*K. Economy*	*I.T.C. Economy*	*P.I. Water-Related*	*K. Water-Related*	*I.T.C. Water-Related*
Household Food Waste	1.0000												
P.I. of Social	-0.1814	1.0000											
K of Social	-0.3445	0.5436	1.0000										
I.T.C. Social	-0.2298	0.5781	0.6459	1.0000									
P.I. of Environment	-0.3490	0.5831	0.3627	0.4148	1.0000								
K of Environment	-0.3757	0.3878	0.3787	0.3866	0.7231	1.0000							
I.T.C. Environment	-0.3811	0.5899	0.4869	0.5511	0.6768	0.5683	1.0000						
P.I. of Economy	-0.3202	0.5458	0.4150	0.3867	0.6045	0.4919	0.6389	1.0000					
K. of Economy	-0.3401	0.4556	0.4933	0.5001	0.5388	0.5777	0.5839	0.6774	1.0000				
I.T.C. Economy	-0.2973	0.4132	0.3201	0.4203	0.3399	0.3385	0.5741	0.5464	0.4639	1.0000			
P.I. of Water-Related	-0.3030	0.4716	0.4568	0.4649	0.5861	0.5217	0.5885	0.5360	0.5970	0.3377	1.0000		
K of Water-Related	-0.2728	0.4155	0.4954	0.4798	0.5078	0.5191	0.5376	0.4801	0.5996	0.2952	0.8212	1.0000	
I.T.C. Water-Related	-0.2814	0.4613	0.4387	0.5750	0.4405	0.3709	0.6159	0.4825	0.4455	0.4825	0.5199	0.5495	1.0000

The correlation coefficients for household food waste and awareness of the social dimensions indicate weak to moderate negative correlations (-0.1814, -0.3445, -0.2298). The correlation coefficients for household food waste and awareness of the environmental dimensions indicate moderate negative correlations (-0.3490, -0.3775, -0.3844). The correlation coefficients for household food waste and awareness of the economic dimensions indicate moderate negative correlations (-0.3202, -0.3401, -0.2973). Finally, the correlation coefficients for household food waste and awareness of the water-related dimensions indicate moderate to weak negative correlations (-0.3030, -0.2728, -0.2814). Every single correlation coefficient highlighted is statistically significant at the 95% confidence level, indicating that the observed relationship is unlikely to occur due to chance (*See Appendix 3*).

Overall, the correlation matrix between food waste awareness and household food waste has observed negative correlations, indicating that as the tendency to throw away edible food increases, there is a trend of less food waste awareness. However, it is necessary to conduct further analysis because while the correlation analysis yields statistically significant results and indicates the presence of a relationship between the dependent and independent variables, it cannot establish causation.

It is also important to note that the correlations between the different dimensions of awareness are all positive moderate or moderate-to-strong correlations. The strongest positive correlations on the matrix are the following:

- Knowledge of social implications and intent to change behavior to improve social implications: 0.6459.
- Perceived importance of environmental implications and knowledge of environmental implications: 0.7231.
- Perceived importance of environmental implications and intent to change behavior to improve environmental implications: 0.6768.

- Perceived importance of economic implications and knowledge of economic implications: 0.6774.
- Perceived importance of water-related implications and knowledge of water-related implications: 0.8212.

These correlations indicate that the more the respondents perceive importance on environmental, economic, and water-related pillars, generally the more knowledge they have on the respective topics. This indicates that their awareness is structured primarily through their knowledge. Furthermore, for social awareness, knowledge of social implications is more correlated with intent to change their behavior. This could indicate that even if they perceive social implications as important, they are more willing to change their behavior if they have more knowledge on the topic.

4.2.3. Correlation Analysis between Household Food Waste and Sociodemographic Factors

This analysis answers the third sub-question, to what extent do socio demographic factors influence household food waste, of the research. The researcher developed another correlation matrix between sociodemographic factors and household food waste (*See Figure 19*). In general, the research suggests that every sociodemographic factor analyzed has a very weak correlation with Household Food Waste.

Figure 19. Correlation Matrix of Sociodemographic Factors & Household Food Waste

	Household Food Waste	*Gender*	*Nationality*	*Education*	*Age*	*Children in Household*	*Number of People in Household*	*Access to Compost Bin*
Household Food Waste	1.0000							
Gender	0.0187	1.0000						
Nationality	0.1028	-0.1275	1.0000					
Education	-0.2301	0.0105	0.1561	1.0000				
Age	-0.2710	-0.0292	0.0270	0.1200	1.0000			
Children in Household	0.1338	-0.1295	0.0558	-0.0315	0.2356	1.0000		
Number of People in Household	0.2354	-0.1122	0.0746	-0.0213	-0.0652	0.5843	1.0000	
Access to Compost Bin	-0.1223	-0.0240	0.0161	-0.0718	0.2341	0.0944	-0.0326	1.0000

The correlation coefficient for gender is a very weak positive correlation (0.0187). The correlation coefficient for household food waste and nationality also concluded a very weak positive correlation (0.1028). Age and education-level have a weak negative correlation at (-0.2710) and (-0.2301), meaning that the younger and less-educated, the higher the Household Food Waste, respectively. While this aligns with previous literature suggestions around education, the researcher expected to see stronger correlations. Further research is needed to understand if this correlation is weaker in highly developed countries. Only Education and Age were deemed statistically significant using p-values (*See Appendix 4*).

Households with or without children also indicate a very weak positive correlation of 0.1338, which confirms the research, if slightly, that households with children tend to waste more food than households without children. The number of people in a household also shows a weak positive correlation of 0.2354, with a similar implication that the greater number of people in a household, the more food wasted. Both correlation coefficients are statistically significant at the 95% confidence level (*See Appendix 4*).

Finally, the correlation coefficient of accessibility to compost indicates a weak negative correlation of -0.1223 and is statistically significant at the 95% confidence level (*See Appendix 4*). This result indicates that the less accessibility, the more food is wasted. This correlation reiterates figures 10 and 11, which demonstrate that if accessibility for compost bins was larger, then more people would compost and waste less food, therefore reinforcing the importance of accessibility of compost bins throughout the city. It is important to note that the correlations here indicate weak relationships, and therefore need further analysis to determine causation.

Between the sociodemographic factors, the correlation matrix shows one moderate positive correlation between children in a household and the number of people in the household (0.5843), with the rest being weak or very weak correlations.

Overall, none of the correlation analyses thus far has produced any substantial positive or negative correlations, this could be because the correlations are simply due to chance or because there are further variables that are needed to explain the relationships. Correlation analysis cannot determine causal relationships and thus further analysis is needed.

4.3. Multilinear Regression Results & Analysis

Multiple Linear Regression Analysis (herein also referred to as regression or multilinear regression) is conducted to understand the relation between a dependent variable, Household Food Waste, and two or more independent variables.

4.3.1. Notes on Sample Size, n, and limitations of Microsoft Excel

It is important to disclose that the built-in regression analysis tools in Microsoft Excel require complete data. In the dataset collected there were the following anomalies:

- Respondent #40 failed to respond to the survey question about over-purchasing food.
- Respondent #190 failed to respond to the survey question about their intent to change behavior for social implications.

- Respondent #326 failed to respond to the survey question about their perceived importance of economic implications.
- Respondent #336 failed to respond to two survey questions, the first about their knowledge of environmental implications, and the second about their intent to change their behavior for environmental implications.
- Respondent #345 failed to respond to the survey question about their intent to change behavior for environmental implications as well.
- Respondent #348 failed to respond to the survey question regarding their household food waste.

Although the researcher collected the intended number of respondents for the sample size (361), to be able to conduct regression analysis, some of the respondents' answers had to be excluded.

To account for the dependent variable in this study is Household Food Waste, respondent #348 had to be excluded from all of the regressions performed. Therefore, reducing the sample size in all regression models with the dependent variable Household Food Waste from 361 to 360. None of the respondents failed to answer questions regarding their socio demographic factors. Therefore, the sample size for the regressions between sociodemographic factors and household food waste was 360. Only one respondent failed to answer questions related to food waste behaviors (respondent #40), therefore the sample size for the regressions between food waste behaviors and household food waste became 359. For the regression models of food waste awareness and household food waste, four respondents failed to answer questions, therefore the sample size was reduced to 360 to 355. For all regression models conducted to optimize results, either selectively within one of the predictors or among all possible independent variables, a sample size of 355 was chosen. It is worth nothing, the research cross-verified the implication the different sample sizes for sociodemographic (360) and behaviors (359), with the final sample size (355) and found the differences to be negligible and unimportant (less than .005% impact on R-squared).

Another important limitation of Microsoft Excel is that the maximum number of independent variables that can be tested in a single regression is 16, meaning that not all independent variables (25) could be tested simultaneously. The researcher concluded this was an acceptable trade-off, given that a model with that many independent variables was not conducive to this research. First, the sample size perhaps was too small for such a complicated model.

Furthermore, as described in Limitations (Chapter 5), using a Likert Scale as dependent and independent variables limits the degrees of freedom and interpretation of the model.

4.3.2. Notes on Interpreting Multiple Regression

The data analyzed shows which of the variables carries statistical significance. Statistical significance can be measured using a P-Value equal to or under 0.05, in other words a confidence level of 95%.

The ‘goodness of fit’ in regression models is measured using additional statistical measures R-squared and Adj R-squared. These statistical measures indicate the proportion of variance in the dependent variable that can be explained by the independent variables in the model (Smith, 2015). The values range from 0.0 to 1.0, where 0 indicates that none of the variation can be explained by the model, and 1 wherein all the variation can be explained. This can also be expressed as a percentage. Therefore, the higher the value, the better fit the model is. Adj R-squared is a fitted version of R-squared that accounts for the number of independent variables and the sample size, thus ensuring more validity to the proportion of variance shown in R-squared (Smith, 2015). Given that all models explored are linear and used a limited number of independent variables, the research understood R-squared as the most appropriate measure.

The minimum number to determine the goodness of fit varies by field of study, variables studied, validity, reliability, and central tendencies of the data. For highly controlled environments, 0.90 is deemed a minimal standard, while social sciences might find 0.50 as a “good fit”. Given this study is attempting to explore predictors of human behavior, more accurately self-reported behaviors, the researcher deemed 0.50 as an excellent fit. This is in line with the novelty of the study as determined by research aims, scope, objectives, and methodology.

Multiple regression analysis can result in several problems that alter the data, including multicollinearity and overfitting. Multicollinearity happens when several of the independent variables have a high correlation with each other in the regression model, making it difficult to interpret which one of the variables influences the dependent variable (Bhandari, 2020). As was explored in the previous section, only two pairs of independent variables were deemed to be ‘strong’ which were Perception of Importance and Knowledge of Environment and Water-Related, respectively. To avoid multicollinearity, these two pairs were always included in regressions with other factors.

Overfitting is a problem that occurs when the statistical model is too complex and begins to describe the random error in the data rather than the relationships between variables (Frost, 2017). To avoid overfitting, the researcher focused on only relevant predictors and ensured that there were not too many degrees of freedom in the models. Both problems can lead to misleading R-squared values, regression coefficients, and p-values, which in turn, can cause an incorrect analysis of the statistical significance of a relationship. Furthermore, the researcher never attempted to further manipulate the data, which could have resulted in narrowing the variance or drastically reducing the sample size. Such manipulation might have built a more predictive model but exposed the research to potential overfitting. Some discarded options were averaging results of Food Waste Awareness by pillar or dimension or using dummy variables to segregate the variables, respectively. The latter was discarded namely due to the use of the Likert scale.

4.3.3. Total Multiple Linear Regressions Performed

Combinations in regression refer to the selection of variables where the order does not matter. For this study, wherein there are 25 variables, the combination of regressions possible is 33,554,431. This number is inconceivable and furthermore, unnecessary for the purpose of this study. For this reason, a table was created below to show the number of iterations regression models run (*See Table 8*).

Table 8. Multiple Regression Summary of Iterations

Dependent Variable - Household Food Waste

Regression Models	Total Iterations Run	Iterations Statistically Significant	Iterations w/ R-squares above 40%
Only Behaviors (4 IV)	6	6	2
Only Awareness (12 IV)	20	4	0
Only Sociodemographic (8 IV)	13	2	0
Sociodemographic & Behavior	3	1	2
Sociodemographic & Awareness	3	2	0
Behavior & Awareness	6	5	2
Optimized	5	2	5
Total	**56**	**22**	**11**

In order to be methodical, the researcher conducted in total 56 different regressions. The first three categories are meant, by complementing the correlation matrices above, to answer the three sub-questions. The subsequent three seeked to identify how the different predictors, when mixed together, influenced the dependent variable, while the fourth optimized all the available independent variables.

The table below illustrates the 21 statistically significant (SS), defined by models where all independent variables had p-values less than or equal to 0.05 (*See Table 9*).

Table 9. Summary Table Main Results of Regression Analysis

Sample size n = 355	**Household Food Waste versus…**				
Food Waste Behaviors	Over purchasing food Planning meals Storing food improperly Expiration date	Over purchasing food Storing food improperly Expiration date	Over purchasing food Storing food improperly Planning meals	Over purchasing food Planning Meals Expiration Date	Storing Food Improperly Planning Meals Expiration Date
P-value	SS	SS	SS	SS	SS
R^2	42.2%	38.6%	37.5%	38.0%	39.0%
Food Waste Awareness	Perceived Importance (4 Pillars)	Knowledge of (4 pillars)	Intent to Change (4 pillars)	Social (3 dimensions)	Environment (3 dimensions)
P-value	3/4	2/4	1/4	1/3	2/3
R^2	15.1%	19.66%	15.60%	11.77%	18.77%
Food Waste Awareness	Economy (3 dimensions)	Water-Related (3 dimensions)	All Awareness (12 IV)	Sustainability (9 IV)	Most Optimized (OptAw1)
P-value	2/3	2/3	2/12	3/9	SS
R^2	13.91%	11.23%	24.88%	24.47%	23.37%
Sociodemographic Factors	Socio (8 IV)	Access to Compost Bin Reasons for Not Composting	Nationality Education Age Number of People in household	N/A	N/A
P-value	4/8	NV	SS		
R^2	19.61%	1.77%	17.38%		
Optimized Pairs	Optimized Behavior & Awareness	Optimized Behavior & Sociodemographic	Optimized Awareness & Sociodemographic	N/A	N/A
P-value	SS	SS	SS		
R^2	46.1%	44.6%	27.2. %		
Optimized All Variables	ALL Variables (4 Behaviors; Nationality, Education, Age, No. Household; P.I. Soc, K. Soc., K. Env, ITC Env, ITC Eco)	Number of People in household Over purchasing food Planning meals Storing food improperly Expiration date Knowledge of environment	Planning meals Over purchasing food Storing food improperly Expiration date Perceived importance of environment Education Knowledge of social Perceived importance of social	N/A	N/A
P-value	8/13	SS	SS		
R^2	48.5%	45.8%	47.5%		

4.3.4. Multilinear Regression of Food Waste Behaviors and Household Food Waste

Regression analysis matches the findings present in the correlation analysis, being that the measured Food Waste Behaviors have the strongest influence over the dependent variable. Immediately, the Four Behaviors rendered a model that was SS, with an R-squared value of 42.5%. When adjusted to the final sample size, n=355, the R-squared value dropped to 42.2%.

To test whether any single Behavior had an excessively strong influence, the research modeled four additional regressions, excluding one behavior each. While all remained SS, all dropped below 40% with a range between 37.5%-39.0%. This suggests that all four Behaviors contribute to the robustness of the model, and thus can predict more accurately, despite weak reliability, the variance of the dependent variable.

4.3.5. Multilinear Regression of Food Waste Awareness and Household Food Waste

The researcher was surprised to learn that Food Awareness had a very weak relation with Food Waste. Despite performing the most amount of regressions, no model resulted in an R-square higher than 24.9%. That model combined all 12 independent variables 3/12 values that were SS. The researcher must conclude that ultimately in isolation, one cannot predict Food Waste using Awareness indicators. This lack of linear relation does not suggest a lack of causation. Further research must be undertaken to explore how measurements of awareness can predict actual (not self-reported) Household Food Waste.

When the researcher dissected the regressions by pillars and dimensions, there was no improvement to the model. In general, individual dimensions performed slightly better with a range of 15.2%-19.7%, while individual pillars had a range of 11.3%-18.8%. The two worst performing pillars, individually, were Economy and Water-Related, meaning in the context of this study, participants were more aware of Environment and Social externalities from Food Waste.

To test these tendencies, the researcher performed six regressions cross-sectionalizing each pair of pillars, in total 6 predictors. As expected, the best performing was Environment & Social, which had a R-square of 23.1% and 4/6 p-values. Economy & Social and Environment & Water-Related each had 3/6 SS p-values and approximately 19.1% R-square. This is rather intuitive, that participants' awareness is biased towards one direction of the pillars, but not confirmed in the correlation. The second highest of all relations measured had an R-square

24.5%, combining 9 variables belonging to the traditional three pillars of sustainability (Social, Environment and Economy). Water-related regressions performed poorer under any combination, perhaps because education on the issue is more novel and not-as-relevant in Europe.

Using the p-values that were consistently SS, the researcher modeled an optimized regression with five variables (P.I. & K. Social, K. & ITC. Environment and ITC Economy) which was SS with an R-squared of 23.4%. Three other optimizations, reducing to only two variables, all performed progressively worse; matching the trend in Behavior that multiple variables mildly improved performance. As such, this five-variable model is the most predictive. This matches the correlations finding that K. Social and K. & ITC Environment as the three strongest (though moderate-to-weak) correlations.

4.3.6. Multilinear Regression of Sociodemographic Factors and Household Food Waste

Of the three studied predictors, sociodemographic had the weakest relation. The trend continued that the largest R-square is present with the most independent variables (8) with a value of 19.6%. The optimized model using the only four SS variables (Nationality, Education, Age and Number of People in Household) resulted in a slightly weaker relation at 17.4%.

In retrospect, as limitations will further explore, a glaring omission is income, which as per the literature review is the best predictor of quantity of Food Waste. Gender, as expected, was not predictive, given it is perhaps the most randomly collected of the sociodemographic variables collected.

The researcher was surprised to learn that neither compost variable was SS, always reducing the model's R-squared when included. In-fact it had the weakest of all studied regressions at 1.7%. This does not align with correlation matrix of all variables where accessibility to compost and reasons to compost had the highest, bar-none, correlation. This suggests that multicollinearity in a negative influence may be present. Further research is needed to understand.

4.3.7. Household Food Waste and Optimized Combinations

Given the limitation of Excel (regressions with at most 16 variables), the researcher approached finding an optimized formula from two methods. The first was to use regressions between two sets of predictors, Behavior & Awareness, Behavior & Sociodemographic and Awareness & Sociodemographic. Each was optimized by reducing the amount of variables, until all remaining variables in the model were SS. The R-squared and number of variables at the end were: 44.6% and 6, 46.1% and 7, 27.2% and 6, respectively. Unsurprisingly, the worst combination was the last, given that it did not include Behavior - the best predictor. As expected, the better of the remaining was Behavior and Awareness. This model included the four Behavior variables and the three strongest (from correlation) variables from Awareness and improved the Behavior-only model by 3.9%. For a sample size of n=355, this seems minor, but extrapolated to the wider Struisenberg or Rotterdam, this improvement might matter. Though it is beyond the scope of this study to test that theory.

To find the most optimized using all available predictors, the SS variables from individual analysis (subsections above) and combination (paragraph above) were tested. The subsection optimized resulted in the highest R-square of 48.5%, but only 8/13 variables were SS. With all SS, the R-squared was 46.6% with 4 behavior, number of people in Household and Knowledge of Environment. The alternative methodology found a different most optimized model, with an R-squared of 47.6% and 8/8 SS variables, including 4 behaviors, education, K. and P.I. Social and P.I. Environment. Further analysis beyond scope must be carried out to understand which is most predictive.

Chapter 5: Conclusions

This chapter presents a comprehensive overview of the study's findings. Drawing upon the results, the conclusion includes interpretations, limitations, and recommendations for future research.

5.1. Main Findings

Main Research Question

To what extent do food waste predictors influence household food waste in Rotterdam?

This study concludes that the predictors studied had a mild influence on household food waste in Rotterdam. The discussion in Chapter 4, as well as limitations discussed below, highlight potential reasons why the statistical significance is undermined.

However, regression and correlation analysis does conclude that six to eight of the twenty-four independent variables do have more impact in predicting and describing household food waste. In the context of a social scientific study, these meet the criteria to be moderately influential.

1. To what extent do food waste behaviors influence household food waste?

Food Waste behavior has by-far the most influence of household food waste, as was seen by the moderate correlation and interpreted as significant in the regression analysis.

2. To what extent does food waste awareness influence household food waste?

Food Waste Awareness has medium influence on household food waste, though the findings were inconclusive. Three factors, in particular Knowledge of Environment, Knowledge of Social and Intent to Change Environment, had the most influence, as evidenced by their contribution to robustness in regression models and strongest relative correlation.

a. Do pillars influence household food waste?

For most analysis performed, Environment and Social outweighed Economic factors. Unsurprisingly, awareness of Water-Related was the least influential.

b. Do awareness dimensions influence household food waste?

The findings were again inconclusive, but knowledge seemed to have been the most consistently influential. At times

3. To what extent do sociodemographic factors influence household food waste?

Sociodemographic factors studied had the least amount of influence on household food waste. A few correspond with existing literature review, such as Age, Gender and Nationality. Others did not match, such as availability to compost, number of household residents and if household has children, suggesting further study is required to understand the discrepancy and uniqueness of Rotterdam.

5.2. Practical Implications of the Study

It is important to acknowledge that this study did provide some valuable insights and information. Firstly, the demographic information about composting. The data collected demonstrated that the proportion of residents who have access to compost bins use them accordingly. With this information, the municipality should consider reintroducing compost bins throughout the city to combat food waste ending up in landfills and help attain its goal of reaching a circular economy by 2050.

Furthermore, the analysis indicated that household food waste mainly occurs when people perform food waste behaviors. Therefore, relevant stakeholders should consider implementing more campaigns focused on reducing the over-purchasing of food at grocery stores, or how to properly store different foods to avoid waste. Stakeholders could also work with the grocery stores to teach residents how to properly comprehend expiration dates on different food labels. Planning meals in advance proved to be a behavior that reduced food waste, thereby another campaign could be made to teach this habit to residents.

While food waste awareness did not explain a substantial amount of variation in household food waste, it did demonstrate a discernible influence. Most noteworthy was that of knowledge. Therefore, there should be more effort toward educating the public on the pillars of food waste. By providing educational programs for the residents about the negative consequences of food waste, the city could in theory reduce the amount of food waste generated per household.

Since the data did not observe very significant relationships between sociodemographic factors and household food waste, the municipality could also focus on widespread random campaigning. The study did not discern any specific demographic to focus on and therefore their campaigning resources can be used across the board.

5.3. Limitations of Study

There are a series of discrepancies found in the data analysis that could be due to a variety of limitations, inherent to the design, collection, or analysis.

5.3.1. Design of Survey

The Likert scale was used in the survey to measure household food waste, food waste behaviors and food waste awareness. Although it was used for accessibility purposes such as translating the nominal data into STATA or Microsoft Excel, it did come with its set of limitations. To begin, Likert scales do not explain in detail or provide reasoning behind the responses the individuals have. Furthermore, Likert-type variables used in regression analysis can lead to lost information or bias (Owuor, 2001). The key limitation here is that the assumption that the data is continuous. This can be a reason why the reported R-squared or coefficient correlations can be underestimated.

Additionally, the google form did not offer an option to indicate what every point on the Likert Scale represented. Thus, the researcher could only describe what 1 and 5 represented, i.e., “1 = Never” and “5 = Always”. While this may have been easily discernible, it allowed the plausible answers to become more subjective to the respondent. This data was beneficial for correlation and regression analysis but made it difficult to visualize the descriptive analytics. In addition, while the researcher chose a specific perspective from which to extrapolate the pillars, dimensions, and behaviors, it is possible that each respondent might have inherent biases towards that specific perspective, thus diminishing both the reliability and validity (i.e., a very personal experience with a methane leak might heavily skew their perception of environment or their understanding that methane is *more* environmental than pollution).

Crucially, the study did not measure the sociodemographic of income level, therefore omitting an indicator that many prior studies have used to measure household food waste. This omission might have been more indicative than other measurements taken.

5.3.2. Reliability

Due to the constrained time frame of this research study, it was important to find feasible random sample data. Therefore, the use of the neighborhood of Struienberg was used, to allocate for only 10% of the population. However, 361 people is not proportionate to the 1,018,000 people that live in Rotterdam. Therefore, the sample data collected is an extremely small representation of the entire population, thereby influencing the reliability of the data. In order to provide concrete recommendations to the city of Rotterdam regarding food waste management, a comprehensive census would need to be done.

The researcher must acknowledge that decreasing the sample size from 361 to 355 for the purpose of regression analysis might have rendered slightly different results from the previous correlation analysis. Furthermore, given the circulation of fliers and mobility, it is possible that some respondents were not confined the established geographical scope of Struienberg. Finally, there is the element of random selection; it is possible that the outreach engagement was bias towards a younger population, more male, or education-level than truly representative.

5.3.3. Validity

This research study used the 12 different variables to measure awareness. In the attempt to provide a well-rounded data collection, the analysis for food waste awareness was made more difficult. Perhaps the analysis of data collection could have been better interpreted with fewer variables, such as solely knowledge.

A limitation of the survey method is that the data was self-reported by the respondents. In this capacity, the respondents could have provided an inaccurate representation of their household food waste, food waste behaviors, or their food waste awareness. In addition to the always present risk of participants being purposefully dishonest, bias is common, thus there is a tendency to overestimate knowledge by those who are not knowledgeable while underestimate knowledge by those who are. Distortions could have been mitigated against by asking verification questions such as reverse coding (opposite meaning questions to check against random), attention checks and known facts could have been asked to assess the motives and attention of participants. The survey could have also tested knowledge of the participant, rather than the self-perception of knowledge of the participant.

Another limitation of the data could be the increased complexity of the variables. There was a total of 25 variables to measure, thereby providing many possibilities for correlation and regression analysis but also increasing the chances of overfitting or multicollinearity.

5.3.4. Data Analysis

The researcher chose to use a few of the most well-known tools in statistical analysis, but perhaps other parameters or tools would have been more appropriate for the purposes of this objective. For instance, Covariance, nonlinear multiple regression among others could have been explored.

While the researcher was tempted to explore the relationships between the independent variables themselves (i.e., change the dependant variable), this analysis might have rendered interesting insight but did not align with the set-out scope, aims, or objectives of the research.

5.4. Recommendations for Further Research

All these limitations indicate suggestions for further or future research. For more accurate results, it would be recommended to do an audit of the food waste of the households instead of self-reporting. Adding to this, it would be more effective to measure the awareness of implications before and after a form of intervention was introduced. Thereby measuring all the same variables in this study with more accuracy. Furthermore, including more variables in the analysis of determinants influencing food waste, for instance instead of nationality, more focus on cultural or personal preferences and their influence on food waste. Analyzing specific cultural preferences of food on Dutch residents, even measuring what specific foods are being wasted more than others could provide further information crucial to reducing food waste. Another recommendation for future research is to use another conceptual framework than Stimulus Organism Theory such as Theory of Planned Behavior to measure these predictors similarly to what previous studies have done. Such as measuring perceived social benefits and their influence on food waste, this could provide an essential part of the research that was not included in this study: *why* do people waste food?

5.5. Concluding Remark

The premise of the study was to indicate which, if any, and to what extent, potential predictors influence household food waste. Beyond that, the study wanted to highlight the severity of such a rectifiable dilemma and hopefully provide the necessary context to continue this dialogue both academically and societally. While the predictors were not as explanatory as the researcher assumed they would be, the study maintains the discourse that household food waste begins with consumer behavior and should be a priority in waste management. In conclusion, this research hopes to bring to the forefront the deep-seated necessity for action on household food waste.

Bibliography

Abdelradi, F. (2018). Food waste behaviour at the household level: A conceptual framework. *Waste Management*, *71*, 485–493. https://doi.org/10.1016/j.wasman.2017.10.001

Adrin Hetharie, J., Surachman, A., Hussein, A., & Puspaningrum. (2019). *SOR (Stimulus-Organism-Response) Model Application In Observing The Influence Of Impulsive Buying On Consumer"s Post-Purchase Regret*. Retrieved from http://www.ijstr.org/final-print/nov2019/Sor-stimulus-organism-response-Model-Application-In-Observing-The-Influence-Of-Impulsive-Buying-On-Consumers-Post-purchase-Regret.pdf

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Aktas, E., Sahin, H., Topaloglu, Z., Oledinma, A., Huda, A. K. S., Irani, Z., … Kamrava, M. (2018). A consumer behavioural approach to food waste. *Journal of Enterprise Information Management*, *31*(5), 658–673. https://doi.org/10.1108/jeim-03-2018-0051

Ananda, J., Karunasena, G. G., Mitsis, A., Kansal, M., & Pearson, D. (2021). Analysing behavioural and socio-demographic factors and practices influencing Australian household food waste. *Journal of Cleaner Production*, *306*, 127280. https://doi.org/10.1016/j.jclepro.2021.127280

Ananda, J., Karunasena, G. G., & Pearson, D. (2023). Has the COVID-19 pandemic changed household food management and food waste behavior? A natural experiment using propensity score matching. *Journal of Environmental Management*, *328*, 116887. https://doi.org/10.1016/j.jenvman.2022.116887

Archip, B. C., Banatean-Dunea, I., Petrescu, D. C., & Petrescu-Mag, R. M. (2023). Determinants of Food Waste in Cluj-Napoca (Romania): A Community-Based System Dynamics Approach. *International Journal of Environmental Research and Public Health*, *20*(3), 2140. https://doi.org/10.3390/ijerph20032140

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. https://doi.org/10.3390/su7066457

Attiq, S., Danish Habib, M., Kaur, P., Junaid Shahid Hasni, M., & Dhir, A. (2021). Drivers of food waste reduction behaviour in the household context. *Food Quality and Preference*, *94*, 104300. https://doi.org/10.1016/j.foodqual.2021.104300

Aydin, A. E., & Yildirim, P. (2021). Understanding food waste behavior: The role of morals, habits and knowledge. *Journal of Cleaner Production*, *280*, 124250. https://doi.org/10.1016/j.jclepro.2020.124250

Barclay, E. (2013, June 6). When You Waste Food, You're Wasting Tons Of Water, Too. Retrieved June 30, 2023, from NPR website: https://www.npr.org/sections/thesalt/2013/06/06/189192870/when-you-waste-food-youre-wasting-tons-of-water-too#:~:text=Tiny%20Desk-

Bhandari, A. (2020, March 19). Multicollinearity | Causes, Effects and Detection Using VIF (Updated 2023). Retrieved from Analytics Vidhya website: https://www.analyticsvidhya.com/blog/2020/03/what-is-multicollinearity/#:~:text=Multicollinearity%20occurs%20when%20two%20or%20more%20independent%20variables%20have%20a

Block, L. G., Keller, P. A., Vallen, B., Williamson, S., Birau, M. M., Grinstein, A., … Tangari, A. H. (2016). The Squander Sequence: Understanding Food Waste at Each Stage of the Consumer Decision-Making Process. *Journal of Public Policy & Marketing*, *35*(2), 292–304. https://doi.org/10.1509/jppm.15.132

Broshuis, L. (2021, April 19). Food waste among Dutch students: motivations and barriers to behave conscientiously towards food waste. Retrieved March 30, 2023, from essay.utwente.nl website: http://essay.utwente.nl/86099/

Carolan, M. S. (2021). What is driving consumer food waste: Socio-material assemblages of household consumption practices. *Appetite*, *166*, 105478. https://doi.org/10.1016/j.appet.2021.105478

CBS. (2023, February 26). Struisenburg Data. Retrieved July 12, 2023, from AllCharts.info website: https://allcharts.info/the-netherlands/neighbourhood-struisenburg-rotterdam/

Ceravolo, R., Coletta, G., Miraglia, G., & Palma, F. (2021). Statistical correlation between environmental time series and data from long-term monitoring of buildings. *Mechanical Systems and Signal Processing*, *152*, 107460. https://doi.org/10.1016/j.ymssp.2020.107460

Chen, R. S., & Kates, R. W. (1994). World food security: prospects and trends. *Food Policy*, *19*(2), 192–208. https://doi.org/10.1016/0306-9192(94)90069-8

Chengqin, E. K., Zailani, S., Rahman, M. K., Aziz, A. A., Bhuiyan, M. A., & Gazi, Md. A. I. (2022). Determinants of household behavioural intention towards reducing, reusing and recycling food waste management. *Nankai Business Review International*. https://doi.org/10.1108/nbri-01-2022-0011

Chinie, C., Biclesanu, I., & Bellini, F. (2021). The Impact of Awareness Campaigns on Combating the Food Wasting Behavior of Consumers. *Sustainability*, *13*(20), 11423. https://doi.org/10.3390/su132011423

Corona, B., Shen, L., Reike, D., Rosales Carreón, J., & Worrell, E. (2019). Towards sustainable development through the circular economy—A review and critical assessment on current circularity metrics. *Resources, Conservation and Recycling*, *151*, 104498. https://doi.org/10.1016/j.resconrec.2019.104498

da Cruz, N. F., Rode, P., & McQuarrie, M. (2018). New urban governance: A review of current themes and future priorities. *Journal of Urban Affairs*, *41*(1), 1–19. https://doi.org/10.1080/07352166.2018.1499416

Design Innovation Group. (2015). Onderzoeksrapport “Vuilnis in de flat, inzichten in gedrag afvalscheiding in hoogbouw.” Retrieved April 4, 2023, from VANG Huishoudelijk afval website: https://vang-hha.nl/kennisbibliotheek/onderzoeksrapport-3/

European Environmental Agency. (2020, December 2). The Netherlands country profile - SDGs and the environment — European Environment Agency. Retrieved from www.eea.europa.eu website: https://www.eea.europa.eu/themes/sustainability-transitions/sustainable-development-goals-and-the/country-profiles/the-netherlands-country-profile-sdgs

Fami, H. S., Aramyan, L. H., Sijtsema, S. J., & Alambaigi, A. (2019). Determinants of household food waste behavior in Tehran city: A structural model. *Resources, Conservation and Recycling*, *143*, 154–166. https://doi.org/10.1016/j.resconrec.2018.12.033

Frost, J. (2017, May 26). Overfitting Regression Models: Problems, Detection, and Avoidance - Statistics By Jim. Retrieved from Statistics By Jim website: https://statisticsbyjim.com/regression/overfitting-regression-models/

Gafoor, K. A. (2012). Considerations in the Measurement of Awareness. In *ERIC*. Retrieved from https://eric.ed.gov/?id=ED545374

Gaiani, S., Caldeira, S., Adorno, V., Segrè, A., & Vittuari, M. (2018). Food wasters: Profiling consumers’ attitude to waste food in Italy. *Waste Management*, *72*, 17–24. https://doi.org/10.1016/j.wasman.2017.11.012

Gjerris, M., & Gaiani, S. (2013). Household food waste in Nordic countries: Estimations and ethical implications. *Etikk I Praksis - Nordic Journal of Applied Ethics*, *7*(1). https://doi.org/10.5324/eip.v7i1.1786

Glasow, P. A. (2005). *Fundamentals of Survey Research Methodology*. Retrieved from https://www.mitre.org/sites/default/files/pdf/05_0638.pdf

Graham-Rowe, E., Jessop, D. C., & Sparks, P. (2014). Identifying motivations and barriers to minimising household food waste. *Resources, Conservation and Recycling*, *84*, 15–23. https://doi.org/10.1016/j.resconrec.2013.12.005

Halloran, A., Clement, J., Kornum, N., Bucatariu, C., & Magid, J. (2014). Addressing food waste reduction in Denmark. *Food Policy*, *49*, 294–301. https://doi.org/10.1016/j.foodpol.2014.09.005

Hansmann, R., Mieg, H. A., & Frischknecht, P. (2012). Principal sustainability components: empirical analysis of synergies between the three pillars of sustainability. *International Journal of Sustainable Development & World Ecology*, *19*(5), 451–459. https://doi.org/10.1080/13504509.2012.696220

Heale, R., & Twycross, A. (2015). Validity and Reliability in Quantitative Studies. *Evidence Based Nursing*, *18*(3), 66–67. Retrieved from https://ebn.bmj.com/content/18/3/66

Hebrok, M., & Boks, C. (2017). Household food waste: Drivers and potential intervention points for design – An extensive review. *Journal of Cleaner Production*, *151*(151), 380–392. https://doi.org/10.1016/j.jclepro.2017.03.069

Hu, S. (2020, July 20). Composting 101. Retrieved from NRDC website: https://www.nrdc.org/stories/composting-101#whatis

Ilakovac, B., Cerjak, M., & Voca, N. (2020). Why do we waste food? In-depth interviews with consumers. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 1–15. https://doi.org/10.1080/15567036.2020.1787564

Iman, R. (2021, August 12). Rotterdam Unlocked Organic Waste Challenge 2021 Creates Business Opportunities For Three International Startups - NettEnergy, Triple W and Arbios Biotech. Retrieved April 4, 2023, from Unknown website: https://unknowngroup.com/rotterdam-unlocked-2021/

Kuddus, M. A., Tynan, E., & McBryde, E. (2020). Urbanization: a Problem for the Rich and the poor? *Public Health Reviews*, *41*(1).

Langeveld, G. (2018, September 2). Rethinking Rotterdam: Breeding ground for circular food waste concepts. Retrieved March 29, 2023, from Beyond Food Waste website: https://beyondfoodwaste.com/rethinking-rotterdam-breeding-ground-for-circular-food-waste-concepts/#:~:text=About%20one%20third%20of%20the

Li, X., Jiang, Y., & Qing, P. (2023). Estimates of Household Food Waste by Categories and Their Determinants: Evidence from China. *Foods*, *12*(4), 776. https://doi.org/10.3390/foods12040776

Mathisen, T. F., & Johansen, F. R. (2022). The Impact of Smartphone Apps Designed to Reduce Food Waste on Improving Healthy Eating, Financial Expenses and Personal Food Waste: Crossover Pilot Intervention Trial Studying Students' User Experiences. *JMIR Formative Research*, *6*(9), e38520. https://doi.org/10.2196/38520

Mondéjar-Jiménez, J.-A., Ferrari, G., Secondi, L., & Principato, L. (2016). From the table to waste: An exploratory study on behaviour towards food waste of Spanish and Italian youths. *Journal of Cleaner Production*, *138*, 8–18. https://doi.org/10.1016/j.jclepro.2016.06.018

Morone, P., Koutinas, A., Gathergood, N., Arshadi, M., & Matharu, A. (2019). Food waste: Challenges and opportunities for enhancing the emerging bio-economy. *Journal of Cleaner Production*, *221*, 10–16. https://doi.org/10.1016/j.jclepro.2019.02.258

Neff, R. A., Spiker, M. L., & Truant, P. L. (2015). Wasted Food: U.S. Consumers' Reported Awareness, Attitudes, and Behaviors. *PLOS ONE*, *10*(6), e0127881. https://doi.org/10.1371/journal.pone.0127881

Nicewicz, R., & Bilska, B. (2022). The Impact of the Nutritional Knowledge of Polish Students Living Outside the Family Home on Consumer Behavior and Food Waste. *International*

Journal of Environmental Research and Public Health, *19*(20), 13058. https://doi.org/10.3390/ijerph192013058

Otero, G., Gürcan, E. C., Pechlaner, G., & Liberman, G. (2018). Food security, obesity, and inequality: Measuring the risk of exposure to the neoliberal diet. *Journal of Agrarian Change*, *18*(3), 536–554. https://doi.org/10.1111/joac.12252

Owuor, C. (2001). *University of Ottawa (1992) B.ED. (Sc)*. Retrieved from https://open.library.ubc.ca/media/download/pdf/831/1.0053856/1#:~:text=Many%20of%20the%20measures%20obtained

Parizeau, K., von Massow, M., & Martin, R. (2015). Household-level dynamics of food waste production and related beliefs, attitudes, and behaviours in Guelph, Ontario. *Waste Management*, *35*, 207–217. https://doi.org/10.1016/j.wasman.2014.09.019

Pinto, R. S., Pinto, R. M. dos S., Melo, F. F. S., Campos, S. S., & Cordovil, C. M.-S. (2018). A simple awareness campaign to promote food waste reduction in a University canteen. *Waste Management*, *76*, 28–38. https://doi.org/10.1016/j.wasman.2018.02.044

Ponis, S. T., Papanikolaou, P.-A., Katimertzoglou, P., Ntalla, A. C., & Xenos, Konstantinos. I. (2017). Household food waste in Greece: A questionnaire survey. *Journal of Cleaner Production*, *149*, 1268–1277. https://doi.org/10.1016/j.jclepro.2017.02.165

Principato, L., Mattia, G., Di Leo, A., & Pratesi, C. A. (2020). The Household Wasteful Behaviour framework: a Systematic Review of Consumer Food Waste. *Industrial Marketing Management*, *93*. https://doi.org/10.1016/j.indmarman.2020.07.010

Quested, T. E., Marsh, E., Stunell, D., & Parry, A. D. (2013). Spaghetti soup: The complex world of food waste behaviours. *Resources, Conservation and Recycling*, *79*, 43–51. https://doi.org/10.1016/j.resconrec.2013.04.011

Reisch, L., Eberle, U., & Lorek, S. (2013). Sustainable food consumption: an overview of contemporary issues and policies. *Sustainability: Science, Practice and Policy*, *9*(2), 7–25. https://doi.org/10.1080/15487733.2013.11908111

Reynolds, C., Goucher, L., Quested, T., Bromley, S., Gillick, S., Wells, V. K., … Jackson, P. (2019). Review: Consumption-stage food waste reduction interventions – What works and how to design better interventions. *Food Policy*, *83*(0306-9192), 7–27. https://doi.org/10.1016/j.foodpol.2019.01.009

Ribbers, D., De Pelsmacker Geuens, M., Pandelaere, M., & van Herpen, E. (2022). Development and Validation of the Motivation to Avoid Food Waste Scale. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4068191

Roodhuyzen, D. M. A., Luning, P. A., Fogliano, V., & Steenbekkers, L. P. A. (2017). Putting together the puzzle of consumer food waste: Towards an integral perspective. *Trends in Food Science & Technology*, *68*, 37–50. https://doi.org/10.1016/j.tifs.2017.07.009

Rotterdam: total population 2008-2018 | Statistic. (2018). Retrieved from Statista website: https://www.statista.com/statistics/753250/total-population-of-rotterdam/

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*(182), 978–991. https://doi.org/10.1016/j.jclepro.2018.02.030

Schmitt, V. G. H., Cequea, M. M., Neyra, J. M. V., & Ferasso, M. (2021). Consumption Behavior and Residential Food Waste during the COVID-19 Pandemic Outbreak in Brazil. *Sustainability*, *13*(7), 3702. https://doi.org/10.3390/su13073702

Scoones, I. (2007). Sustainability. *Development in Practice*, *17*(4-5), 589–596. https://doi.org/10.1080/09614520701469609

Seberini, A. (2020). Economic, social and environmental world impacts of food waste on society and Zero waste as a global approach to their elimination. *SHS Web of Conferences*, *74*(03010), 03010. https://doi.org/10.1051/shsconf/20207403010

Secondi, L., Principato, L., & Laureti, T. (2015). Household food waste behaviour in EU-27 countries: A multilevel analysis. *Food Policy*, *56*, 25–40. https://doi.org/10.1016/j.foodpol.2015.07.007

Shaw, P., Smith, M., & Williams, I. (2018). On the Prevention of Avoidable Food Waste from Domestic Households. *Recycling*, *3*(2), 24. https://doi.org/10.3390/recycling3020024

Smith, G. (2015). *Essential statistics, regression, and econometrics*. Waltham, Massachusetts: Academic Press.

Soma, T., Li, B., & Maclaren, V. (2020). Food Waste Reduction: A Test of Three Consumer Awareness Interventions. *Sustainability*, *12*(3), 907. https://doi.org/10.3390/su12030907

Stancu, V., Haugaard, P., & Lähteenmäki, L. (2016). Determinants of consumer food waste behaviour: Two routes to food waste. *Appetite*, *96*(96), 7–17. https://doi.org/10.1016/j.appet.2015.08.025

Talwar, S., Kaur, P., Kumar, S., Salo, J., & Dhir, A. (2022). The balancing act: How do moral norms and anticipated pride drive food waste/reduction behaviour? *Journal of Retailing and Consumer Services*, *66*, 102901. https://doi.org/10.1016/j.jretconser.2021.102901

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. https://doi.org/10.1016/j.ijhm.2021.103033

Timmermans, B., & Cleeremans, A. (2015). *How can we measure awareness? An overview of current methods*. Retrieved from https://axc.ulb.be/uploads/2015/11/15-timmermansoup.pdf

Tyczewska, A., Woźniak, E., Gracz, J., Kuczyński, J., & Twardowski, T. (2018). Towards Food Security: Current State and Future Prospects of Agrobiotechnology. *Trends in Biotechnology*, *36*(12), 1219–1229. https://doi.org/10.1016/j.tibtech.2018.07.008

United Nations. (1987). Sustainability. *United Nations*. Retrieved from https://www.un.org/en/academic-impact/sustainability

United Nations. (2018, May 16). 68% of the world population projected to live in urban areas by 2050, says UN. Retrieved from UN DESA | United Nations Department of Economic and Social Affairs website: https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html#:~:text=Today%2C%2055%25%20of%20the%20world

Vergara, V., & Jammi, R. (2022, April 7). Towards a circular economy: Addressing the waste management threat. Retrieved from ieg.worldbankgroup.org website: https://ieg.worldbankgroup.org/blog/towards-circular-economy-addressing-waste-management-threat

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. https://doi.org/10.1016/j.jenvp.2015.11.007

Wang, J., Li, M., Li, S., & Chen, K. (2022). Understanding Consumers' Food Waste Reduction Behavior—A Study Based on Extended Norm Activation Theory. *International Journal of Environmental Research and Public Health*, *19*(7), 4187. https://doi.org/10.3390/ijerph19074187

World Food Programme. (2020, June 2). 5 facts about food waste and hunger | World Food Programme. Retrieved from www.wfp.org website: https://www.wfp.org/stories/5-facts-about-food-waste-and-hunger#:~:text=One%2Dthird%20of%20food%20produced

Yan, X. (2019). *CIRCULAR HOUSEHOLD ORGANIC WASTE TREATMENT IN THE HIGH-RISE RESIDENTIAL BUILDING*. Delft, Netherlands: Integrated Product Design, TU Delft.

Yinuo. (2023, May 21). UN 2023 SDG Summit. Retrieved from United Nations Sustainable Development website: https://www.un.org/sustainabledevelopment/blog/2023/05/un-2023-sdg-summit/

Zamri, G. B., Azizal, N. K. A., Nakamura, S., Okada, K., Nordin, N. H., Othman, N., … Hara, H. (2020). Delivery, impact and approach of household food waste reduction campaigns. *Journal of Cleaner Production*, *246*, 118969. https://doi.org/10.1016/j.jclepro.2019.118969

Zhang, Y., van Herpen, E., Van Loo, E. J., Pandelaere, M., & Geuens, M. (2023). Save near-expired food: Does a message to avoid food waste affect food purchase and household waste prevention behaviors? *Journal of Cleaner Production*, *384*, 135555. https://doi.org/10.1016/j.jclepro.2022.135555

Zhou, X., Yang, J., Xu, S., Wang, J., Zhou, Q., Li, Y., & Tong, X. (2020). Rapid in-situ composting of household food waste. *Process Safety and Environmental Protection*, *141*, 259–266. https://doi.org/10.1016/j.psep.2020.05.039

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Appendix 2. Stata Matrix of Food Waste Behaviors and Household Food Waste

	throwi~d	over_p~d	planni~s	storin~y	expira~e
throwing_a~d	1.0000				
over_purch~d	**0.4257**	1.0000			
	0.0000				
planning_m~s	**-0.3691**	-0.2312	1.0000		
	0.0000	0.0000			
storing_fo~y	**0.5394**	0.4097	-0.3123	1.0000	
	0.0000	0.0000	0.0000		
expiration~e	**0.4791**	0.2763	-0.1491	0.5248	1.0000
	0.0000	0.0000	0.0045	0.0000	

Appendix 3. Stata Matrix of Food Waste Awareness and Household Food Waste

	throwi~d	though~r	knowle~r	intent~r	though~t	knowle~t	intent~t
throwing_a~d	1.0000						
thoughts_o~r	**-0.1814**	1.0000					
	0.0005						
knowledge_~r	**-0.3445**	0.5436	1.0000				
	0.0000	0.0000					
intent_to_~r	**-0.2298**	0.5781	0.6459	1.0000			
	0.0000	0.0000	0.0000				
thoughts_o~t	**-0.3490**	0.5831	0.3627	0.4148	1.0000		
	0.0000	0.0000	0.0000	0.0000			
knowledge_~t	**-0.3775**	0.3878	0.3807	0.3807	0.7238	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000		
intent_to_~t	**-0.3844**	0.5875	0.4898	0.5366	0.6775	0.5698	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
thoughts_o~y	**-0.3202**	0.5458	0.4150	0.3867	0.6045	0.4940	0.6432
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
knowledge_~y	**-0.3401**	0.4556	0.4933	0.5001	0.5388	0.5792	0.5881
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
intent_to_~y	**-0.2973**	0.4132	0.3201	0.4203	0.3399	0.3403	0.5755
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
thoughts_o~e	**-0.3030**	0.4716	0.4568	0.4649	0.5861	0.5233	0.5908
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
knowledge_~e	**-0.2728**	0.4155	0.4954	0.4798	0.5078	0.5203	0.5392
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
intent_to_~e	**-0.2814**	0.4613	0.4387	0.5750	0.4405	0.3689	0.6087
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Appendix 4. Stata Matrix of Sociodemographic Factors and Household Food Waste

	throwi~d	gender	nation~y	educat~n	age_gr~p	househ~n	num_pe~d
throwing_a~d	1.0000						
gender	**0.0187**	1.0000					
	0.7240						
nationality	**0.1028**	-0.1275	1.0000				
	0.0514	0.0153					
education	**-0.2301**	0.0105	0.1561	1.0000			
	0.0000	0.8425	0.0029				
age_group	**-0.2710**	-0.0292	0.0270	0.1200	1.0000		
	0.0000	0.5798	0.6085	0.0226			
households~n	**0.1338**	-0.1295	0.0558	-0.0315	0.2356	1.0000	
	0.0111	0.0138	0.2901	0.5514	0.0000		
num_people~d	**0.2354**	-0.1122	0.0746	-0.0213	-0.0652	0.5843	1.0000
	0.0000	0.0332	0.1573	0.6862	0.2162	0.0000	
compost	**-0.1223**	-0.0240	0.0161	-0.0718	0.2341	0.0944	-0.0326
	0.0203	0.6495	0.7598	0.1735	0.0000	0.0731	0.5370
	compost						
compost	1.0000						

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