Leveraging Analytics to Understand Food Consumption and Waste in Achieving Personalized Nudging

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Abstract

Managing food waste is pivotal in advancing sustainable consumption practices. This study investigates how various factors such as food type, consumer spending, socio-economic characteristics, and demographics correlate with food waste patterns, utilizing data analytics and statistical analysis. Drawing on studies in green information systems (IS) and digital nudging, we propose three strategic nudging designs: pre-existing nudges based on food type characteristics, configurable nudges tailored to demographic and socio-economic profiles, and dynamic nudges responsive to evolving consumer behaviors. These interventions are designed to utilize behavioral insights to promote more sustainable consumer habits and present a novel methodology for substantially reducing food waste.

Keywords: Green IS, Digital nudging, Data analytics, Food waste reduction, Consumer behavior

1. Introduction

Food waste remains a critical global challenge with significant implications for environmental sustainability, economic efficiency, and food security. The Food and Agriculture Organization (FAO) of the United Nations reports that about one-third of all food produced for human consumption is lost or wasted globally. In the UK, for instance, approximately 6.6 million tonnes of household food is wasted each year, which equates to about one-sixth of all purchased food being wasted WRAP (2021). This waste not only represents a missed opportunity to improve global food security but also contributes unnecessarily to greenhouse gas emissions and the misuse of water and land resources. Studies in the sustainability field, for instance, Wharton et al. (2021) provided a comprehensive look at the stages at which food waste occurs, from production to consumption, highlighting the need for targeted interventions.

Drawing on the concept of digital nudging and from the lens of design science, we aim to identify the effective factors that enable the information system, specifically a mobile application, to effectively nudge users towards sustainability and reducing food waste behavior. We worked with IntelliDigest, an organization based in Edinburgh that focuses on enhancing food system sustainability, and their online platform World Food Tracker (WFT)[1] which enables users and producers to balance demand and supply of food. This study aims to answer the question:

- How can green nudging be built to reduce food waste by mapping user behavior and profile?

Using 3121 food shopping records collected from 107 users, we use analytics and statistical methods, including descriptive, correlation and regressions, to understand user behavior in everyday food consumption and waste, and to map their behavior between purchase and waste. We contribute to the green IS and digital nudging literature by unpacking and mapping factors at individual user level that are critical for sustainable food consumption.

2. Related Work

2.1. Green IS in the food sector

The literature on green IS and sustainability management provides a crucial starting point to

[1] IntelliDigest Limited – World Food Tracker https://intellidigest.com/services/food-waste-tracker/

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understand the interplay between firms, technology, and individuals in the transition for net zero (e.g., Leidner et al. (2022)). Green IS research explores the development, implementation, and application of IS and explains how they lead to increased environmental sustainability (Brendel et al., 2022). Studies have examined the conceptualization (Melville, 2010), drivers (Hanelt et al., 2017) and impacts (Nishant et al., 2017) of green IS at organizational level. More recently, Leidner et al. (2022) examined the form of interorganizational organizing and the supply chain context. It is however less clear regarding how green IS representation and advocacy make an impact at individual level and to individual green IS users.

From the perspective of design science, despite efforts in conceptualizing and explaining green IS to address environmental sustainability (Leidner et al., 2022; Melville, 2010), our understanding regarding the design of green IS and how to create artefacts to attain sustainability goals remains limited (Brendel et al., 2022). Current individual-oriented studies focus on developing artefacts that influence and change actions towards more sustainable behaviors, via means such as providing users with sustainability-related information and therefore triggering more environmentally friendly actions (Brendel et al., 2022). Efficient artefacts that deliver suitable messages to users are important for triggering sustainable actions.

Relating the green IS to the avoidance of food waste, we argue that when individuals (i.e. technology users) interact with IS (such as mobile apps), the formation and representation of their behaviors towards environmental sustainability could impact their attitudes and behaviors towards reducing food waste. This is based on that on one hand, in the food sector, the use of technology, particularly mobile applications, plays a significant role in addressing food waste at the consumer (as technology user) level. Research indicates that mobile apps can help manage food purchases and inventory, potentially reducing waste by improving consumer planning and awareness. For example, Haas et al. (2022) highlight the potential for mobile apps to assist households in tracking food usage, thus preventing waste through better management and consumption reminders. On the other hand, Melville (2010) reviewed behavior studies and identified that IS plays a crucial role in shaping user beliefs and attitudes towards environmental sustainability. How food related information is presented could be closely connected to how individual users' attitudes and behaviors are shaped towards food waste reduction.

2.2. Nudging Strategy in Technological Interventions

Our research relates to the literature on digital nudging. A nudge refers to an attempt to influence decision-making without affecting people's range of choices and without noticing that they have been influenced (Kretzer & Maedche, 2018). Adopting the original concept of nudging to the digital environment, digital nudging refers to the use of user-interface (such as applications and websites) design elements to guide people's behavior (Weinmann et al., 2016). Nudging strategies, which involve subtle changes to the environment to promote more sustainable behavior without force, have been identified as effective in influencing consumer behavior. In recent years, IS researchers have studied the potential application of digital nudging in the online decision-making environment. For example, Xiao et al. (2022) developed a dynamic model examining the influence of digital nudging on digital services' consumer behavior. Mirbabaie et al. (2021) studied the use of digital nudging in managing emergency and disaster communication on social media.

Green nudging techniques and methods are introduced into system design. For example, Tiefenbeck et al. (2018) demonstrated how users can be nudged toward reducing resource consumption by removing salience bias and introducing real-time feedback, leading to behavioral changes. Mirbabaie et al. (2023) examined two nudging strategies, default nudge and social norm nudge, in steering sustainable purchase decisions in choosing fashion products. Studies by Von Kameke and Fischer (2018) demonstrate how nudges can help reduce food waste by encouraging consumers to make more mindful choices about food purchases and consumption. Other intervention and nudge approach in the food sector include receiving information about financial impacts or environmental impacts of avoidable food waste (Shaw et al., 2018), information about leaflet and recycling station Linder et al. (2018), and feedback on how household's residential street performed on food waste recycling in comparison to their neighbourhood (Nomura et al., 2011).

A particular challenge of nudging in reducing individual food waste, differing from prior work, is the variability, size and differences among individual users, which makes it difficult to apply nudges effectively across all demographics. Applying data analytics in developing specific nudges could enable recognition of such differentiation. For instance, leveraging data and algorithmic models, systems can create more customized and responsive digital nudges based on the identified patterns of user behaviors and actions (Sadeghian & Otarkhani, 2023). In the food sector, the use of data analytics to understand and predict individual food consumption and waste is increasingly recognized as crucial in designing effective interventions (Cicculo et al., 2022). By analyzing purchasing and waste patterns, researchers can identify key factors leading to food waste and thereby propose interventions for waste reduction. In this study, we explore how data-driven insights can inform strategies tailored to specific individual behaviors and contexts, informing digital green nudging as an intervention to reduce food waste.

3. Method

3.1. World Food Tracker (WFT) app and data collection

We collaborated with IntelliDigest, a company that supports stakeholders across the food system from farms to individuals in the transition to adopting more sustainable practices in food distribution and consumption. Specifically, we used their WFT application to track individual user's food consumption and waste behavior. To recruit participants, we conducted multiple rounds of engagement activities, including station promotions in food markets, social media promotions, workshop advertisements, and platform recruitment (Prolific). 107 participants were recruited over a six-month period (May to November 2023). Participants used the WSFT app over a two-week period to record their food purchasing, consumption, and waste, along with demographic details such as age, gender, income, household size, and weekly food expenditure.

To ensure recording quality, before the formal data collection, we conducted a pilot study with five users to record their food behavior over two consecutive weeks. The purposes of the pilot study included 1) testing the app's functionality to ensure the web version consistently matched the mobile version; 2) verifying that the recording process in user instructions could logically progress to track users' food purchase, consumption, and waste stages.

We adopted several analytical methods to assess food consumption and waste patterns alongside demographic, socio-economic factors, and behaviors. Particularly, descriptive statistics were applied to provide a baseline understanding of the data, highlighting food waste distribution across food types, user groups, and worst versus best performers in food wastage. Correlation analysis helped identify relationships between different variables, such as the link between socio-economic status regarding food waste performance. Additionally, we calculated correlation coefficients to quantify the strength and direction of these relationships. This approach allowed us to gather insights into the factors influencing food waste, which we then used to make informed design suggestions for effective food waste nudging strategies.

3.2. Data processing and analytic methods

Figure 1 demonstrates the data cleaning and analysis procedures that we used to analyze food consumption and wastage. Initially, raw files are converted into a standardized raw data format, such as CSV, which includes a unique user code and detailed records of food items purchased. Each food item is then manually classified into various categories such as Vegetables, Fruits, Dairy, Meat/Fish, etc., to organize the data by food types and sub-types. The workflow also involves calculating the duration from purchase to expiration (Expire Days) and from purchase to wastage (Waste Days) using the recorded purchase, expiry, and wasted dates. Additionally, the process captures the amount of food purchased and the amount wasted, with efforts to clean and standardize this data through coding and manual adjustments to ensure accuracy in quantifying and unit conversion. This detailed analysis helps in understanding patterns in food utilization and wastage, which can inform food policy, consumer education, and environmental sustainability efforts.

In the analysis, we implemented a variety of analytical methods to investigate the patterns of food consumption and waste, as well as the influence of demographic, socio-economic factors, and behaviors. Descriptive statistics provided an initial overview, mapping out the distribution of food waste among different food types and user groups, including identifying the worst and best performers in terms of wastage. Through correlation analysis, we examined relationships between socio-economic characteristics and waste habits. We also computed correlation coefficients to accurately assess the strength and direction of these interactions. This holistic analytical approach helped us uncover key insights into the driving factors behind food waste. The detailed findings from these analyses, which form the basis for targeted design recommendations aimed at optimizing food waste reduction initiatives, are presented in the subsequent section.

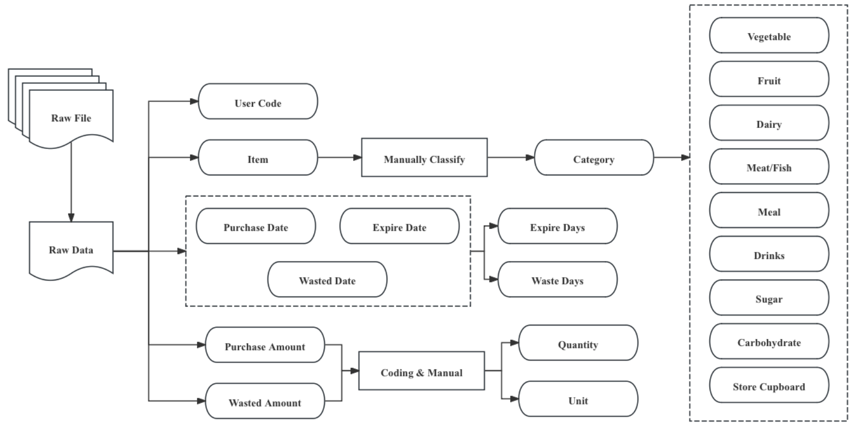


Figure 1. Data Cleanse & Feature Engineering

4. Results

4.1. Overview of user food waste data

Derived from the WFT app, our analysis reveals variations in food waste across demographics and categories through four key areas: overall user waste distribution, breakdown by category, detailed percentages by type, and patterns among the best and worst wasters. The distribution in Figure 2 reveals that most users waste less than 20% of their purchased items, showing general proficiency in food utilization. However, a tail of high-waste users points to the need for targeted interventions, such as educational content on food preservation and analyzing demographic and consumption patterns for personalized nudging strategies. Figure 3 categorizes food waste by types, highlighting that perishable goods like fruits and vegetables (32% and 26%, respectively) and dairy (20%) have the highest waste levels, followed by carbohydrates (18%), indicating spoilage as a significant factor. Strategic notifications about optimal storage methods, reminders for products nearing spoilage, and recipes for using up such ingredients could effectively manage the lifecycle of perishable purchases. Furthermore, variability in food waste rates, as detailed in Figure 4, shows the alignment with the overall analysis in Figure 3 that perishables like fruits, vegetables and dairy have significantly higher waste rates compared to non-perishables. This suggests that spoilage and over-purchasing might be contributing factors even to responsible shoppers. For the worst food wasters (bottom 25%), there also shows a significant chance of purchasing excessive store cupboard items which end up with wasting. Besides, an opposite trend is observed in sugar products, where the less sensible food wasters significantly reduce their waste. This reduction not only demonstrates a conscious effort to manage or prioritize their consumption but may also reflect underlying preferences for these types of foods, influencing how they are purchased and used.

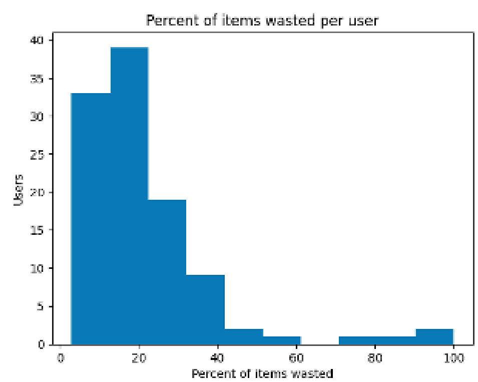


Figure 2. Distribution of Waste among Users

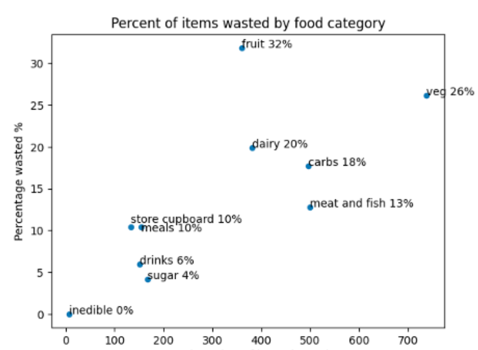


Figure 3. Food Item Waste by Category

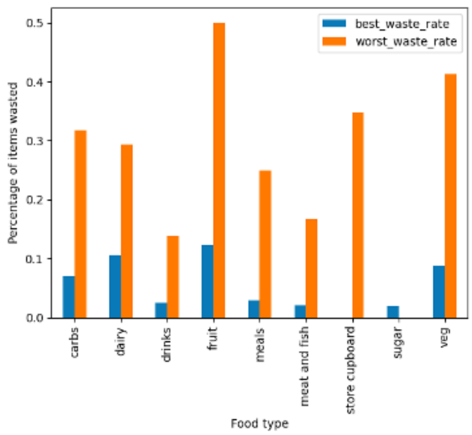


Figure 4. Wasted Food Types of Top 25% vs. Bottom 25% 'Wasters'

4.2. Waste analysis by food category

This analysis reveals significant waste trends in key food categories such as fruits, vegetables, dairy products, and carbohydrates, as highlighted in Figure 3. The waste patterns within these categories are varied, impacted by factors like perishability and consumption habits. Fruit waste is particularly high, with bananas having a notable 43% wastage due to rapid spoilage, in contrast to oranges, which exhibit a lower 18% waste because of their longer shelf life, as shown in Figure 5(a). Similarly, perishable items like salad leaves and herbs exhibit substantial waste rates, such as 62% for salad and spinach, whereas more durable or canned vegetables like potatoes and baked beans show much lower rates of 24% and 9%, respectively, as detailed in Figure 5(b). For the dairy products with short shelf lives, for example cream and dips record high waste percentages of 61% and 43%, indicating the necessity for better storage and consumption planning. Carbohydrates, as shown in Figure 5(d) particularly bakery items such as bread, also display high waste levels, with bread and bread loaves reaching up to 50% and 41% waste, highlighting the misalignment between purchase quantities and actual usage.

4.3. Food consumer profile analysis

Demographic breakdown shown in Figure 6 highlights the intricate relationship between demographic characteristics, socio-economic factors, and individual food waste, indicating the necessity for targeted intervention strategies. Participants are categorized into groups based on demographic characteristics such as gender and age, socio-economic factors like income and household size, and food-related behaviors including weekly food expenditure. This categorization provides insights into the food waste patterns of the best and worst performers.

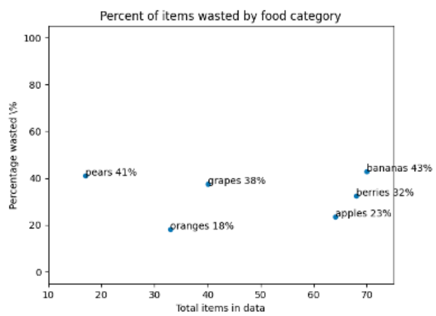
In the analysis of "best vs. worst" waste percentages by gender, as shown in Figure 6(a), 59% are categorized under the best performing group, showing lesser waste, compared to 45% in the worst group. Conversely, females show a reversal in this trend, with only 41% in the best group and a higher 54% in the worst group. This indicates a slight male predominance in efficiency concerning waste management.

Age analysis in Figure 6(b) shows shows a prominent presence in the group of 40–50, with 40.91% in the best category for minimal waste and 45.45% in the worst category for maximum waste, indicating a significant disparity in waste management behaviors within this demographic. The group of 30–40 displays a contrast with less efficiency in waste management. The two age groups of 20–30 and 60+, show a less pronounced representation in the worst category (13.64% and 4.55%, respectively), indicating better waste management practices.

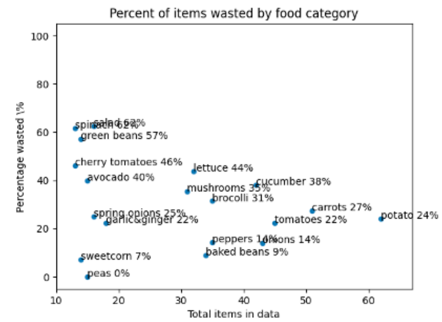
For the factor of income shown in Figure 6(c), notably, the £20,000–£40,000 range appears in both best (40.91%) and worst (27.27%) categories, indicating inconsistent behaviors within this group. Conversely, higher income brackets (£40,000–£60,000 and £60,000+) are represented in the worst category (31.82%), suggesting that greater income does not necessarily lead to better waste practices. Unsurprisingly, the lowest income group (<£20,000) shows lower waste with higher representation in the best category (18.18%) than in the worst (9.09%).

Regarding household size in Figure 6(d), single-person households are better represented in the best category (36.36%) than in the worst (18.18%), indicating more effective waste practices among individuals living alone. Two-person households, while making up a substantial portion of the best (31.82%), also lead the worst category (40.91%), highlighting a contrast in their waste management behaviors. In contrast, larger households, particularly those with five or more members, show minimal variation, with a smaller presence in both best (9.09%) and worst (4.55%) categories, suggesting a consistency in waste management practices.

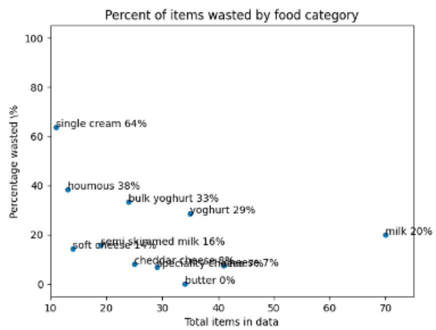
As shown in Figure 6(e), the £50–£100 weekly spending range is heavily represented in both best (50%) and worst (72.73%) groups, indicating a broad spectrum of behaviors from very efficient to quite inefficient for waste management. In contrast, those spending £100–£150 weekly show a moderate presence in the best group (13.64%) but a higher incidence in the worst



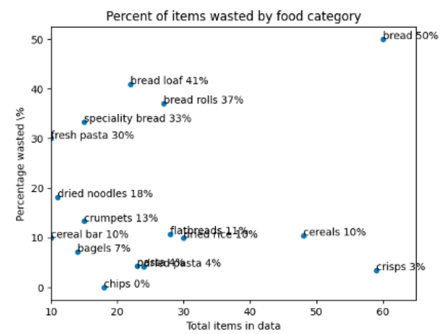
(a) Types of Fruit Wasted



(b) Types of Vegetable Wasted



(c) Dairy Product Wasted



(d) Carbohydrate and Bakery Wasted

Figure 5. Food Waste across Categories

group (22.73%), suggesting less optimal waste practices at higher spending levels. The highest spenders, allocating over £150 weekly, are less represented in both the best (9.09%) and worst (4.55%) groups, implying higher spending is not commonly linked to poor waste management.

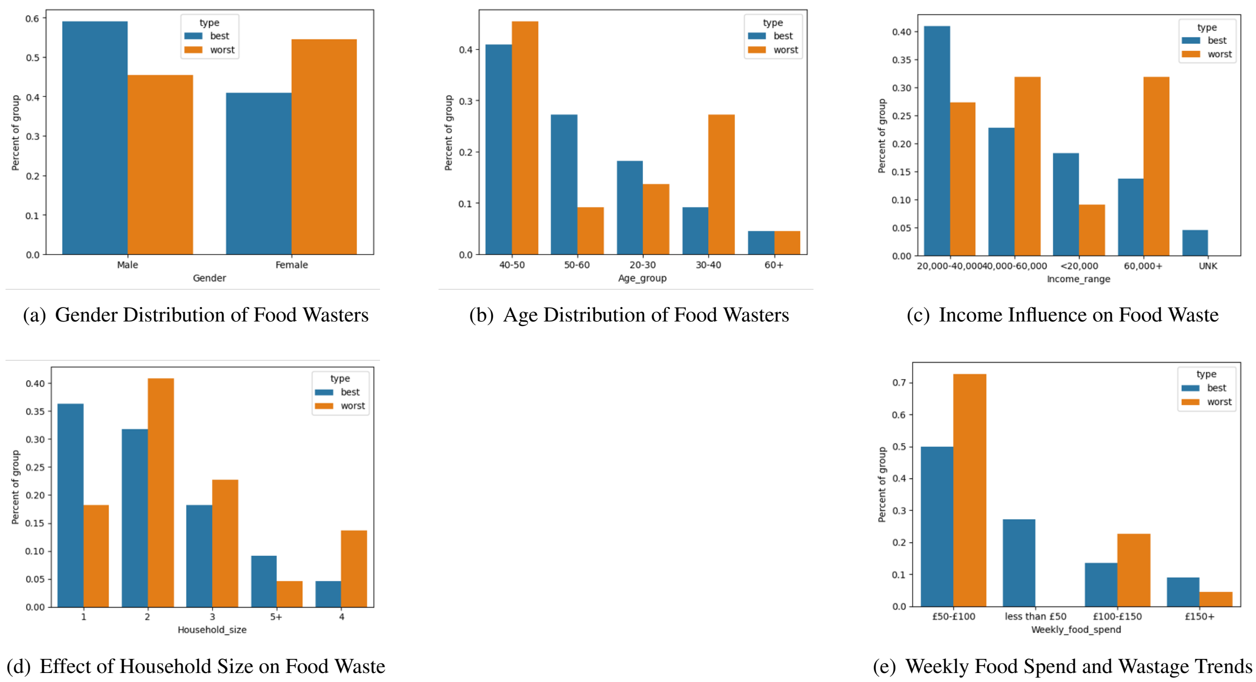
4.4. Regression Analysis of Waste Determinants

We conducted regression coefficients analysis, which provides a comprehensive overview of how various factors correlate with waste production, as shown in Figure 7.

- Food Type: The regression coefficients for fruits (1.0) and vegetables (0.98) are highly positive, due to their perishability and stringent aesthetic standards. Conversely, sugar (-1.0) and drinks (-0.96) indicate less waste, benefiting from longer shelf lives and better packaging. These observations, in alignment with Figure 5, suggest targeted strategies based on food types could effectively reduce waste.

- Food-related Behaviors: Lower spending (under £50) has a negative coefficient (-0.31), whilst spending between £50–£100 shows a positive coefficient (0.38), indicating higher waste levels as the weekly spending increases to this level. However, when the weekly spend increases to £100 or over £150, the coefficients decrease and turn to be the opposite (-0.019 and -0.052). A possible explanation is that increased spending beyond a certain threshold does not necessarily lead to increased purchasing quantity but rather to improved quality.

- Socio-Economic Factors: Two-person households (hh_2) have higher waste (0.21), while households of three and four (hh_3 and hh_4) manage waste better, showing negative coefficients (-0.201 and -0.17). Middle income ranges correlate with increased waste, as evidenced by positive coefficients across £20,000–£40,000 (0.131) and £40,000–£60,000 (0.09) groups. This indicates that individuals in two-person households (hh_2) might typically fall into the £20,000–£40,000 income bracket, which aligns with their slightly higher waste levels. In contrast, households of three and four, showing more efficient waste management, could consist of senior professionals earning incomes above £60,000



(a) Gender Distribution of Food Wasters

(b) Age Distribution of Food Wasters

(c) Income Influence on Food Waste

(d) Effect of Household Size on Food Waste

(e) Weekly Food Spend and Wastage Trends

Figure 6. Profile of Food Wasters

who prioritize efficiency and quality in their consumption habits, thus contributing to lower waste generation.

- Demographic Factors: Age groups such as 30–40 and 40–50 show positive coefficients (0.23 and 0.17 respectively), highlighting an association with increased waste production. These age groups typically encompass active working adults who may have less time for efficient meal planning and thus might generate more waste. However, the age group 50–60 demonstrates better waste management practices (-0.38 as coefficient to waste), might due to more stable lifestyles, higher environmental awareness or better financial security.

4.5. Correlational Analysis of Non-Food Factors

The correlational analysis identified significant positive and negative correlations among non-food variables, such as income range and household size, which strengthens the findings regarding non-food waste determinants. As shown in Figure 8, the correlation matrix visually represents the strength and direction of relationships among user characteristics through color-coded correlations:

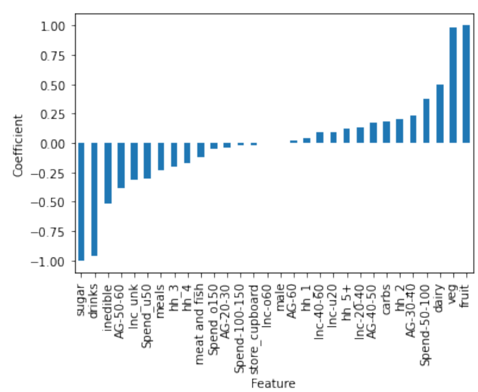


Figure 7. Regression coefficients

Weekly Food Spend vs Income Range: Those in the lower middle income group (£20,000–£40,000) tend to spend the least on food shopping (under £50 per week), which aligns with a positive correlation (+0.42). Given the negative coefficient for this spending group in relation to food waste (-0.305), as shown in Figure 7, it suggests that lower-income individuals, likely more efficient or constrained in their food spending, tend to buy only what they can consume, potentially reducing wastage.

Weekly Food Spend vs Household Size: In addition to income levels, there is a significant correlation between household size and weekly food expenditures. In Figure 8, households of size one which typically spend under £50 weekly have a correlation coefficient of +0.44. This indicates that smaller households generally spend less on food shopping. However, this spending pattern doesn't straightforwardly correlate with their waste patterns. As depicted in Figure 7, waste correlations vary with household size; for example, a household of size one has a small positive correlation with waste (+0.043). This suggests that the spending behavior of smaller households does not necessarily align with their waste generation, pointing to a more complex relationship between spend and waste behaviors.

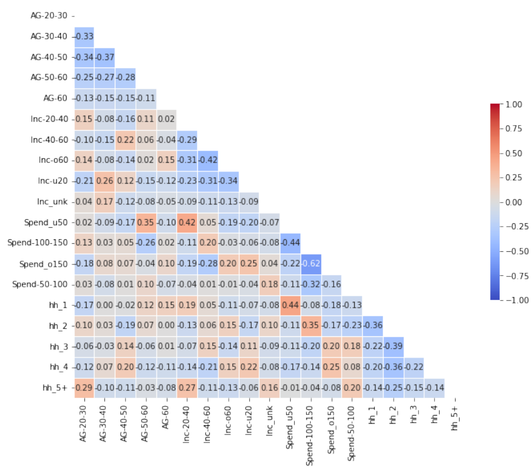


Figure 8. Correlation matrix

5. Discussion

Responding to the research question, we put forward three propositions based on the results and by using the WFT as a demonstrated example. Given the analysis of waste patterns across various food types, spending habits, socio-economic, and demographic factors, the findings provide a solid basis for proposing three distinct nudging designs: pre-existed food nudge, configurable nudge as well as dynamic behavior nudge.

Proposition 1: Pre-existing nudging design should be customized based on food types and perishability to mitigate food waste.

The high waste coefficients for fruits and vegetables indicate significant wastage, primarily due to perishability and aesthetic standards. A pre-existing nudging design could involve color-coded labels or alerts in stores and apps, highlighting perishability to encourage timely consumption or purchase based on near-term use. Figure 9(a) demonstrates an example of such design. Green labels could indicate freshness, while yellow could suggest that the item should be consumed soon, and red might indicate that the item is nearing its spoilage date. This visual nudge aims to make consumers more aware of spoilage timelines at the point of purchase.

This nudging is not directly informed by or related to user behavior. Instead, the information such as food perishability pre-existed in the application database. Wucher et al. (2020) demonstrated the relationship between raising awareness of storage parameters for perishable food as a nudge and lower rates of food waste. Following a similar line of thought, incorporating food types and perishability in nudging design should play a positive role in reminding users of timely food consumption.

Proposition 2: Building a configurable nudging system based on user-centric socio-demographic and socio-economic features is crucial for food waste reduction.

The result shows that waste patterns vary significantly with household size and income levels. For instance, two-person households with a coefficient of 0.21 suggest different waste patterns compared to larger or smaller households. A configurable nudge system could adapt notifications and tips based on user-entered demographic information during app registration. For example, households identified in the £20,000–£40,000 income range might receive customized suggestions for bulk buying or storage practices to reduce waste, while larger households might receive nudges tailored towards meal planning and efficient food use.

Incorporating user socio-demographic and socio-economic background in the design in Figure 9(b) is related to what Mirbabaie et al. (2023) referred to as social norm nudging - presenting users with information suggesting specific options are more socially adopted. For instance, informing users that people with similar income range and household numbers are likely to adopt a certain shopping pattern or behavioral pattern for food waste reduction.

Proposition 3: Incorporating dynamic and responsive elements into nudging designs, based on real-time user behaviors, could be effective in reducing food waste.

This proposition highlights the importance of user-centric and dynamic food waste behavior in nudging design. Observing user behaviors over time can provide insights into spending and consumption patterns that lead to waste. For instance, if a food shopping pattern moving from under £50 to £50–£100 every week (suggesting a higher possibility of wasting), is consistently observed over a period of four weeks, a dynamic nudging system might intervene with tailored

(a) Default nudging design (b) User-centric nudging design (c) Bahavioral nudging design

Figure 9. Proposed nudging designs based in WFT app

suggestions to optimize purchasing decisions and reduce waste. Conversely, if households frequently purchase large quantities of perishable items that lead to waste, the system could trigger nudges for more frequent, smaller purchases or provide recipes that focus on using up what is already at home. The system would adapt based on continuous feedback from user activity, making nudges more personal and timely.

The nudging content provided in Figure 9(c) is dynamic according to the user's timely behavioral pattern, with the purpose of either reinforcing an existing behavior or forming a new behavior. By providing feedback based on user real-time behavior, the nudging helps to remove salience bias and is more likely to result in behavioral changes (Tiefenbeck et al., 2018). This type of nudging design could potentially work well with younger users, as indicated by Von Kameke and Fischer (2018)'s study that younger shoppers tend to rate and react towards proposed nudges better compared to older shoppers. Furthermore, such a design could also include a user feedback loop, allowing customers to decide whether to adopt the suggested nudges in their future food consumption tracking (Lu et al., 2019).

6. Conclusion and Future Work

This study explored the intricate relationships between food waste and various influencing factors including food type, consumer spending, socio-economic characteristics, and demographics, with the aim of informing green nudging design and promoting sustainable food consumption. We identified key patterns influencing food consumption and waste, highlighting the significant roles of perishability and consumer behavior. We propose three innovative nudging designs: pre-existing nudges based on food characteristics, configurable nudges tailored to specific demographic and socio-economic profiles, and dynamic nudges that adapt to changes in consumer behavior over time.

We contribute to the field of green IS and digital nudging by unpacking and mapping factors that are crucial for sustainable food consumption at individual user level, and by proposing potential nudging mechanisms to reduce food waste. Future research could explore additional variables like nutritional factors and lifestyle factors such as physical activity to understand how nutritional content and health-oriented behaviors impact consumer purchasing decisions and waste patterns, and thus impacting relevant nudging strategies. Longitudinal studies could also be conducted to observe long-term effects of nudging interventions on consumer behavior and waste reduction, helping to refine these strategies over time and adapt them to changes in consumer habits and market dynamics. Additionally, incorporating technologies such as machine learning and big data analytics could enhance the predictive capabilities of waste reduction models, enabling more precise and dynamic adjustments to nudging mechanisms.

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