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Exploring Consumer Behavior towards Social Impact Apps for Food Waste Reduction

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Abstract

Food waste is a significant global challenge, with social and environmental implications that demand innovative solutions. Apps like Too Good To Go offer a technological approach to mitigating food waste by connecting consumers with surplus food from local businesses at discounted prices. This study examines consumer behavior toward such apps, focusing on their attitudes, motivations, and barriers to adoption. Using a survey distributed to current users, potential users, and non-users, data were collected on demographics, usage patterns, perceptions, and challenges. Descriptive analysis, behavioral segmentation, and statistical testing revealed several main motivators—such as cost savings, environmental awareness, and convenience—that drive engagement with these apps. We also identified generally positive attitudes toward the technology's potential to reduce food waste, though notable barriers persist, including skepticism about surplus food quality and app usability. Building on these insights, our results show that consumers prioritize substantial discounts of 40% or more and clear indication of food freshness when deciding to adopt and consistently use food waste reduction apps. Additionally, low interest in features associated with loyalty programs and wide variety of dietary options, allow us to save on app development costs and shorten time-to-market. Our findings also allow us to conduct a more targeted marketing campaign, focusing on motivational drivers like convenience, instead of a more generic message.

Keywords

Food Waste, Sustainability, Consumer Motivators, Survey-Based Research

1. Introduction

In an era where environmental sustainability has become a global priority, reducing food waste stands out as a critical challenge. According to the Food and Agriculture Organization (FAO), approximately one-third of all food produced globally is wasted, resulting in significant environmental, economic, and social consequences (Food and Agriculture Organization, 2013). This level of waste contributes to the depletion of natural resources, as vast amounts of water, energy, and land are used to produce food that is never consumed. Additionally, global food loss and waste exacerbate climate change, with estimates suggesting that about 8% of total anthropogenic greenhouse gasses (GHG) emissions can be attributed to food wastage; indeed, if food wastage were a country, it would be the third largest emitting country in the world (Food and Agriculture Organization, 2015). Given these staggering figures, innovative solutions are needed to mitigate food waste at all levels of the supply chain, from production to consumption.

In response to this issue, digital platforms and mobile applications have emerged as effective tools for reducing food waste by redistributing surplus food to consumers. Among these platforms, Too Good To Go (TGTG) has gained prominence as a leading solution. The app connects consumers with restaurants, grocery stores, bakeries, and cafes that have surplus food, allowing them to purchase these items at significantly reduced prices (Too Good To Go, 2021). By enabling businesses to recover some of their costs while preventing edible food from being discarded, TGTG offers a win-win scenario for both businesses and environmentally conscious consumers. Similar initiatives, such as Olio, Karma, and Flashfood, also promote food redistribution through peer-to-peer sharing or direct sales from retailers to consumers (Olio, n.d.; Karma, n.d.; Flashfood, n.d.). However, despite the growing popularity of such apps, their adoption and long-term user engagement remain inconsistent (Harvey, Smith, Goulding, & Branco Illodo, 2020).

While food waste reduction apps present a promising technological intervention, their effectiveness largely depends on user participation. Several factors may influence whether individuals choose to adopt and consistently use these platforms. Consumer motivations, such as financial savings, environmental awareness, and convenience, play a crucial role in app adoption. At the same time, perceived barriers—including concerns about food quality, lack of awareness, and app usability—may deter potential users. Understanding these factors is essential for enhancing the reach and impact of these applications, ultimately helping to reduce global food waste on a larger scale (Derqui & Viachaslau, 2023).

This study aims to examine consumer behavior toward food waste reduction apps, with a particular focus on Too Good To Go using survey-based research. By analyzing users' attitudes, motivations, and barriers to adoption, this research seeks to identify key factors that influence engagement with such apps. The findings from this study will contribute to the development of improved marketing strategies, user experience enhancements, and policy recommendations to promote sustainable consumer practices. Ultimately, this research aims to support the broader effort of reducing food waste by leveraging technology-driven solutions that encourage individuals to make more sustainable choices in their daily lives.

We found that while motivation to use such apps is present, people expect a more concrete set of benefits, such as significant discounts of 40% or more and assurances and transparency regarding the freshness of the food offered by local businesses.

The remainder of the paper is structured as follows. We present the existing research in Section 2. Section 3 discusses our approach to data, including the survey design and approach to analyzing data, including the assessment of the negative space of responses. Section 4 examines attitudes, motivations, and barriers of our potential users, while Section 5 spells out the conclusion of the study.

2. Literature Review and Hypotheses

Mobile applications such as Too Good To Go (TGTG) connect consumers with discounted surplus food, turning potential waste into value. Understanding their business models, consumer behaviors, adoption barriers and suitable research methods is crucial to maximizing impact (van der Haar & Zeinstra, 2019).

Consumer behavior is pivotal. A systematic review of 49 studies showed that lack of planning, over-buying and failure to reuse leftovers are the chief household drivers of waste (dos Santos et al., 2022). The same review links app adoption to three motivations—cost savings, environmental concern and convenience—while highlighting an intention-behavior gap that apps must bridge.

Despite clear benefits, adoption barriers persist. Stangherlin & de Barcellos (2018) categorized obstacles into societal (norms that undervalue food), personal (over-purchasing, reluctance to buy discounted surplus) and behavioral (low awareness). Food-safety skepticism and quality concerns remain major deterrents (Derqui & Viachaslau, 2023).

Methodological work warns that self-report surveys tend to under-state waste and over-state sustainable intentions; behavioral tracking is recommended as a supplement (Ahmed et al., 2021). We revisit this limitation in Section 5.

Hypothesis Development

Prior studies indicate that consumer adoption of surplus-food apps is mainly shaped by (a) pro-environmental motives, (b) perceived monetary benefit, and (c) concern about food safety (dos Santos et al., 2022; Stangherlin & de Barcellos, 2018; Derqui & Viachaslau, 2023). Translating these insights into testable claims, we propose three hypotheses:

Code	Hypothesis	Expected sign
H1	Higher **environmental concern** increases the likelihood that a consumer intends to adopt a surplus-food app.	+
H2	Stronger **perceived cost-savings motivation** increases adoption intent.	+
H3	Greater **food-safety worry** decreases adoption intent.	−

These hypotheses will be evaluated simultaneously in a logistic-regression model that uses the binary adoption-intent variable (0 = unlikely, 1 = likely) as the dependent measure.

3. Data

3.1. Survey Design

To examine consumer behavior toward food waste reduction applications like Too Good To Go (TGTG), this study employs a structured survey methodology using Qualtrics, a widely used online survey platform. The survey is designed to collect both quantitative and qualitative data from a diverse sample of respondents, including current users, potential users, and non-users of food waste reduction apps. By targeting these three groups, the study aims to gain comprehensive insights into the factors influencing app adoption, usage patterns, perceived benefits, and barriers to engagement.

The survey consists of multiple sections, each designed to capture specific aspects of consumer attitudes and behaviors. The structure follows a logical flow, beginning with demographics, followed by usage patterns, motivations, barriers, and perceptions of food waste and technology.

3.1.1. Demographics Tracking

The demographics section gathers key respondent information including Income levels (Figure 1), age, number of children, education level, geographic location, etc. (Figures 2-7). Table 1 below first provides the counts and percentages for each variable; Figures 1-7 then visualize those same distributions. Together, these descriptive data allow us to examine whether certain groups such as younger adults, urban residents, or those with higher education, are likely to adopt food-waste-reduction apps.

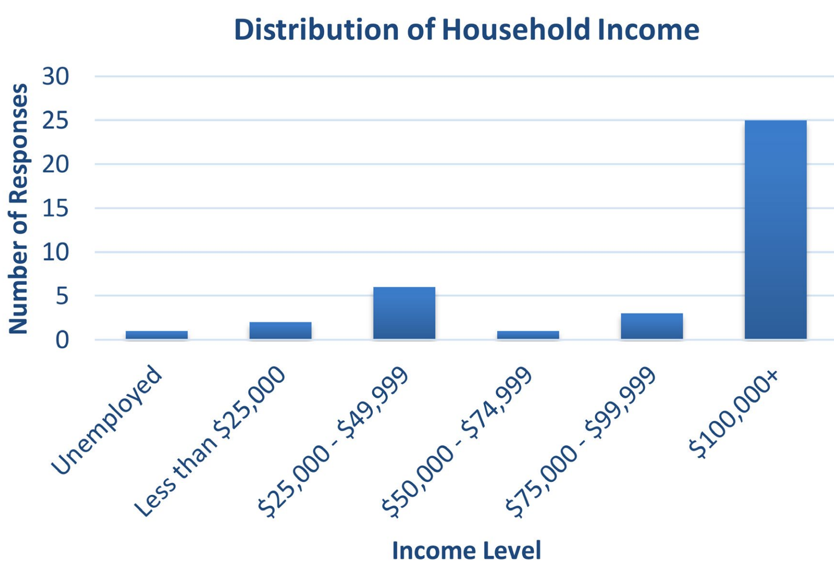

Figure 1. Demographics—income level.

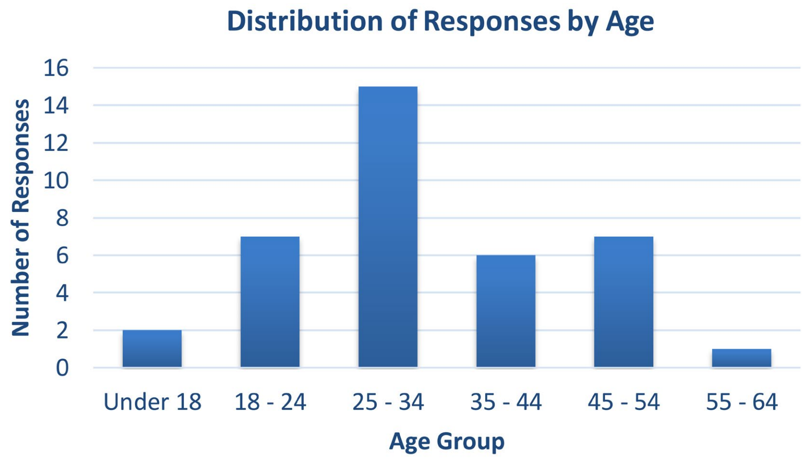

Figure 2. Demographics—age.

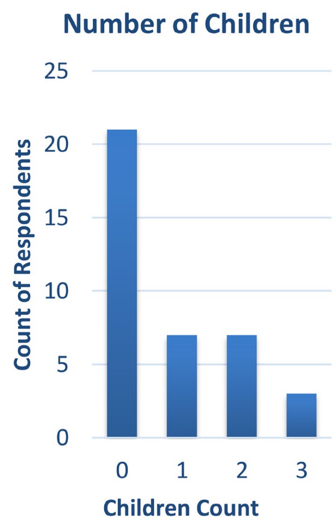

Figure 3. Demographics—# of children.

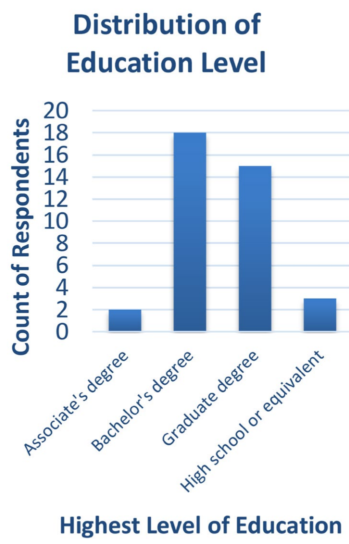

Figure 4. Demographics—education level.

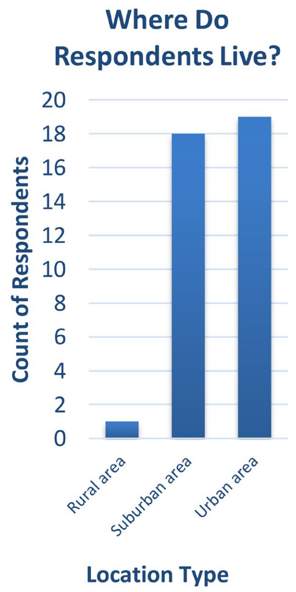

Figure 5. Demographics—geo-location.

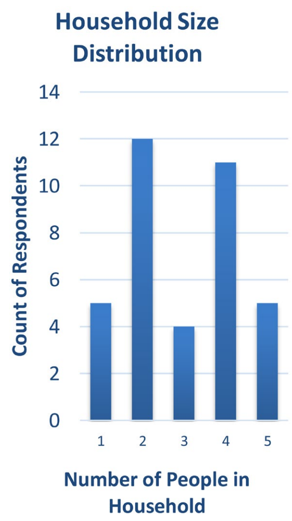

Figure 6. Demographics—household size.

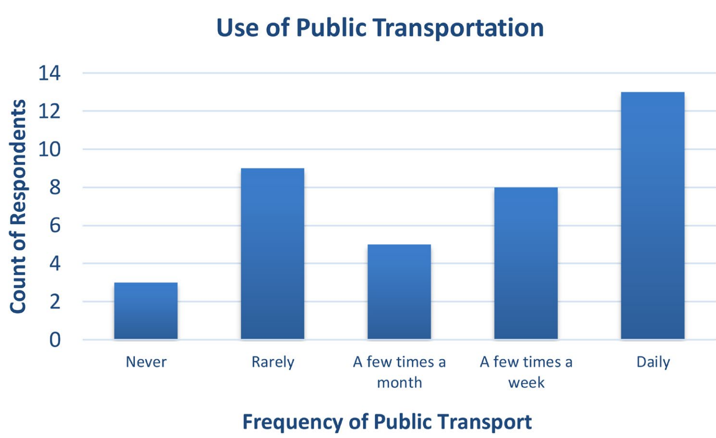

Figure 7. Demographics—use of public transportation.

Table 1. Sample demographics (N = 38).

Variable	Value	# of responses	%
age	Under 18	2	5.3
age	18 - 24	7	18.4
age	25 - 34	15	39.5
age	35 - 44	6	15.8
age	45 - 54	7	18.4
age	55 - 64	1	2.6
age	65+	0	0
household_income	Unemployed	1	2.6
household_income	Less than $25,000	2	5.3
household_income	$25,000 - $49,999	6	15.8
household_income	$50,000 - $74,999	1	2.6
household_income	$75,000 - $99,999	3	7.9
household_income	$100,000+	25	65.8
education_level	Associate's degree	2	5.3
education_level	Bachelor's degree	18	47.4
education_level	Graduate degree	15	39.5
education_level	High school or equivalent	3	7.9
location	Rural area	1	2.6
location	Suburban area	18	47.4
location	Urban area	19	50

3.1.2. Behavioral Patterns, Motivation, and Preferences

For current users of food waste reduction apps, the survey captures their usage patterns by asking about the frequency of app use, types of purchases made (e.g., meals, groceries, baked goods), average spending per transaction, time of day when the app is most frequently used, and how long they have been using the app. This section helps determine whether behavioral trends emerge among active users, such as frequent engagement during evenings or a preference for specific types of food.

The next section focuses on the motivations for app usage, aiming to understand why individuals choose to use food waste reduction apps and what incentives drive their engagement (Figure 8). Respondents indicate the importance of factors such as saving money, reducing personal food waste, supporting local businesses, environmental concerns, and an interest in trying new foods or restaurants. Understanding these motivations helps pinpoint the strongest drivers of adoption, allowing developers and policymakers to enhance marketing and incentive strategies.

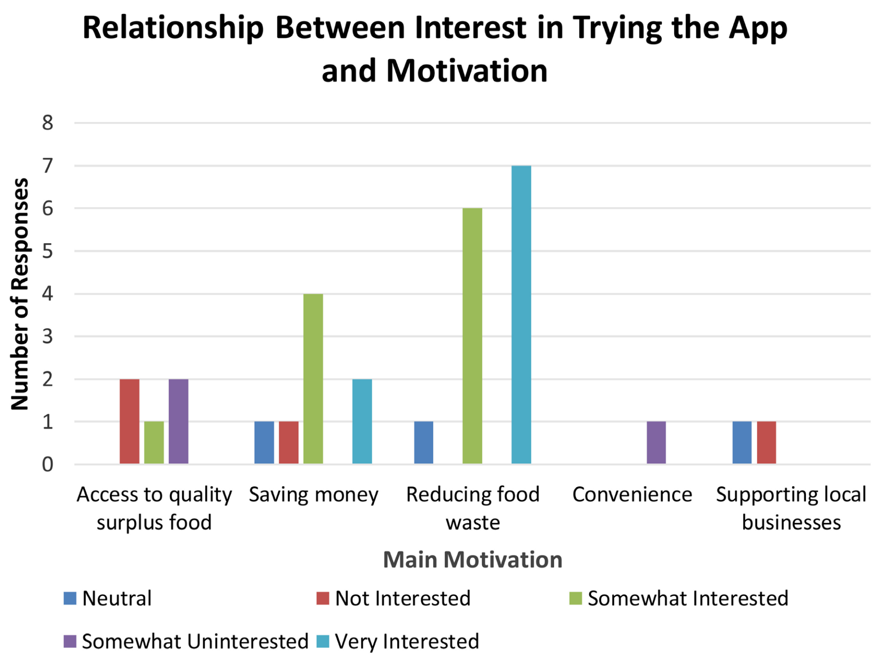

Figure 8. Main motivation drivers.

A number-based approach for examining motivation allows us as researchers to detect patterns that might be less evident when data remains in strictly categorical form. By translating discrete categories (e.g., "Somewhat Interested") into numeric values, it becomes feasible to compute averages, standard deviations, and other statistical measures. This process not only facilitates more precise comparisons across subgroups but also makes it possible to identify subtle shifts in user attitudes toward the app, ultimately providing a richer, more quantifiable perspective on how various motivational factors influence interest levels. We will examine this approach in detail a little later.

The survey also includes a section dedicated to identifying barriers that prevent users from adopting or consistently using food waste reduction apps. This section examines issues such as awareness of the app's existence, perceived inconvenience in using the app, concerns about the quality or freshness of surplus food, trust issues regarding participating vendors, and technical difficulties or usability issues. By analyzing these responses, the study can determine whether issues such as lack of awareness, mistrust in food quality, or technical barriers significantly hinder adoption. The findings will be valuable for informing strategies to improve app functionality and increase user trust.

The final section assesses perceptions of food waste and technology's role in addressing it. Respondents are asked about their beliefs regarding the severity of food waste as an issue, opinions on the effectiveness of technology in reducing food waste, willingness to recommend the app to others, and the perceived impact of personal actions on broader environmental outcomes. This section provides insight into public attitudes toward sustainability, which can help tailor educational initiatives and awareness campaigns promoting food waste reduction.

3.1.3. Distribution Methodology

The survey link circulated through the authors' social-media and e-mail networks, which prevents an exact invitation count; we estimate ≈ 200 potential recipients. Forty-four individuals opened the questionnaire, and 38 met all pre-registered quality filters—full completion, ≥45 s duration, correct attention-check, and complete demographics—yielding the final analytic sample (N = 38). Depending on the invitation estimate, the crude completion rate is 22 % (44/200). Full cleaning steps appear in Online **Appendix B**.

Designed using Qualtrics, the survey follows a dynamic and adaptive structure, allowing follow-up questions to be tailored based on previous responses. If a respondent indicates they have never used a food waste reduction app, they are directed to questions focusing on barriers to adoption rather than usage patterns. If a respondent identifies as a frequent user, additional questions explore satisfaction levels, preferred app features, and potential improvements. This personalized approach ensures relevant data collection, reduces respondent fatigue, and enhances response accuracy.

3.1.4. Quality Control Measures

To ensure data reliability and validity, the survey follows best practices in questionnaire design. Randomized question order is used to minimize response biases, and Likert-scale response options are provided for attitude-based questions to capture nuanced insights. Additionally, the survey undergoes pre-testing among a small pilot group to refine clarity and effectiveness. Open-ended response options are incorporated in key sections to capture qualitative insights and allow respondents to elaborate on their experiences. These responses offer deeper perspectives that may not be fully captured through multiple-choice or scale-based questions.

The structured survey methodology used in this study is designed to provide comprehensive, high-quality data on consumer engagement with food waste reduction apps. By gathering insights into motivations, barriers, and perceptions, the findings will help shape future app development, policy recommendations, and marketing strategies aimed at increasing adoption and promoting sustainable consumer behaviors.

In addition to these measures the data is further cleaned utilizing reusable R scripts. After cleaning, we ran a binary logistic-regression model to evaluate H1–H3, using the recoded adoption-intent variable (intent01, 0 = unlikely, 1 = likely) as the outcome and three predictors—environmental concern (env), cost-savings motivation (cost), and food-safety concern (food_safety_concern). See Online **Appendix B** for additional details.

Exploratory segmentation. For completeness, we ran a mixed-data clustering using Gower distance with a Partitioning-Around-Medoids (PAM) algorithm; a three-cluster solution (average silhouette width = 0.46) is reported in Online **Appendix B**.

4. Results

4.1. Inferential Test of H1 - H3

Inferential test of H1 - H3 (logistic regression) yielded the following results:

- H1 supported: higher environmental concern significantly increased adoption intent ($B = 1.42$, $SE = 0.63$, $z = 2.24$, $p = .025$).
- H2 not supported: cost-savings motivation showed no reliable effect ($B = 0.21$, $SE = 1.11$, $z = 0.19$, $p = .851$).
- H3 partly supported: food-safety concern was negative but fell short of significance ($B = -1.88$, $SE = 1.25$, $z = -1.51$, $p = .133$).

Overall, environmental concern emerged as the only robust predictor of stated adoption intent in this sample ($N = 38$).

4.2. Attitudes

Among the respondents who have prior experience using food waste reduction apps, preliminary findings indicate a generally positive reception and growing sense of routine integration. Many self-identified frequent users note that they have successfully reduced personal waste at home by purchasing surplus meals or groceries at discounted prices (Figure 9). This experience, in turn, fosters increased confidence in the reliability of the platform: users are more willing to recommend the app to friends and colleagues, citing financial savings and environmental impact as two primary benefits. However, some experienced users still mention quality control concerns—especially when perishable items like dairy and produce are close to or past their best-by dates—emphasizing the need for transparent labeling and communication of food freshness. Overall, these active users appear less hesitant about the app's value but continue to desire expanded partnerships with local vendors to broaden the food options available. The graph below indicates that people who have already tried the app believe that these types of applications can definitely make an additional difference in reducing food waste.

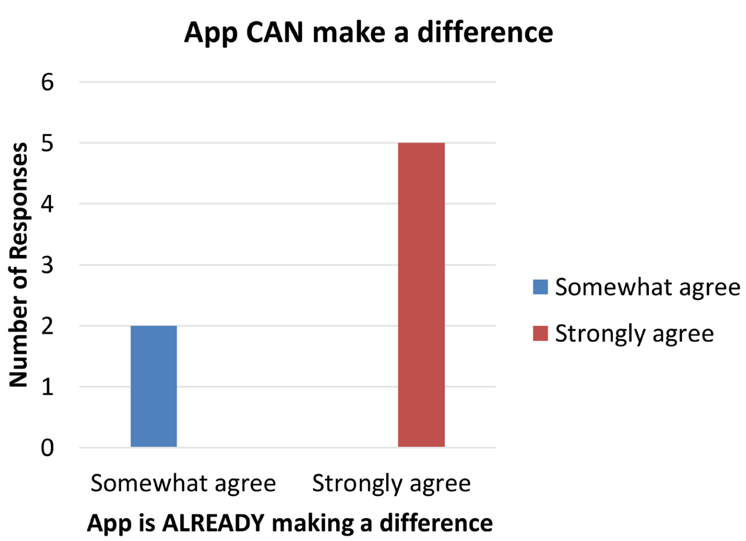

Figure 9. Insights from experienced users.

Extending the question of whether the application stands a chance to make a difference from the overall user population and combining the top two choices of "Very interested" and "Somewhat interested" we get an overwhelming show of support for the app (**Figure 10**).

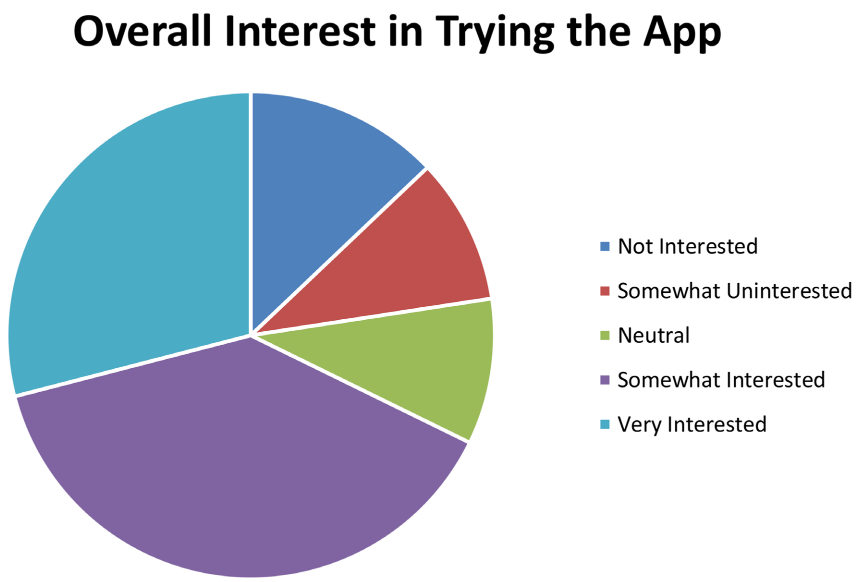

Figure 10. Overall interest in trying the app.

4.3. Motivation

One of the primary motivations behind user engagement with food waste reduction apps is the potential for reducing food waste and cost savings (**Figure 8**). Participants often highlight that discounted surplus food encourages them to try new products or restaurants they might otherwise avoid, while also reducing their grocery bills. Particularly in times of economic pressure, the ability to purchase meals or groceries at significantly lower prices is a clear incentive. This cost benefit is closely tied to increased environmental awareness; many users indicate they feel a sense of personal responsibility for curbing food waste and appreciate the tangible impact of rescuing surplus items that would otherwise be discarded.

Another important driver is convenience, reflecting how easily the process fits into users' daily routines. Apps that provide clear navigation, real-time updates on available surplus, and quick pickup times see higher adoption and ongoing use. This ease of use also reduces barriers for those who may be environmentally conscious but lack the time or energy to research other waste-prevention strategies. Ultimately, when cost, environmental concern, and convenience converge, the motivation to embrace food waste reduction apps strengthens, leading to more consistent and widespread use.

4.3.1. Why Examine the Lower-Ranked Features?

In the context of feature rankings for a food waste reduction app, much attention naturally gravitates toward top priorities—such as discounted prices or improved food quality and safety. However, understanding which features users consistently rank lowest can be equally enlightening. By identifying elements that receive "least-important" scores, we can discover how to refine our focus and potentially transform less-popular features into future growth opportunities rather than immediate selling points.

4.3.2. Evidence from Ranking Data

A careful review of the right-hand side of the bar chart—where ranks 6, 7, and 8 appear—reveals that "More dietary options" and "Loyalty rewards/discounts" both attract disproportionately higher volumes of low-priority scores compared to other features. Although some respondents may still appreciate dietary flexibility or point-based rewards, these features do not significantly drive overall adoption. Instead, participants tend to place more value on lower prices for surplus food, food quality & safety, and simplified app navigation (Figure 11).

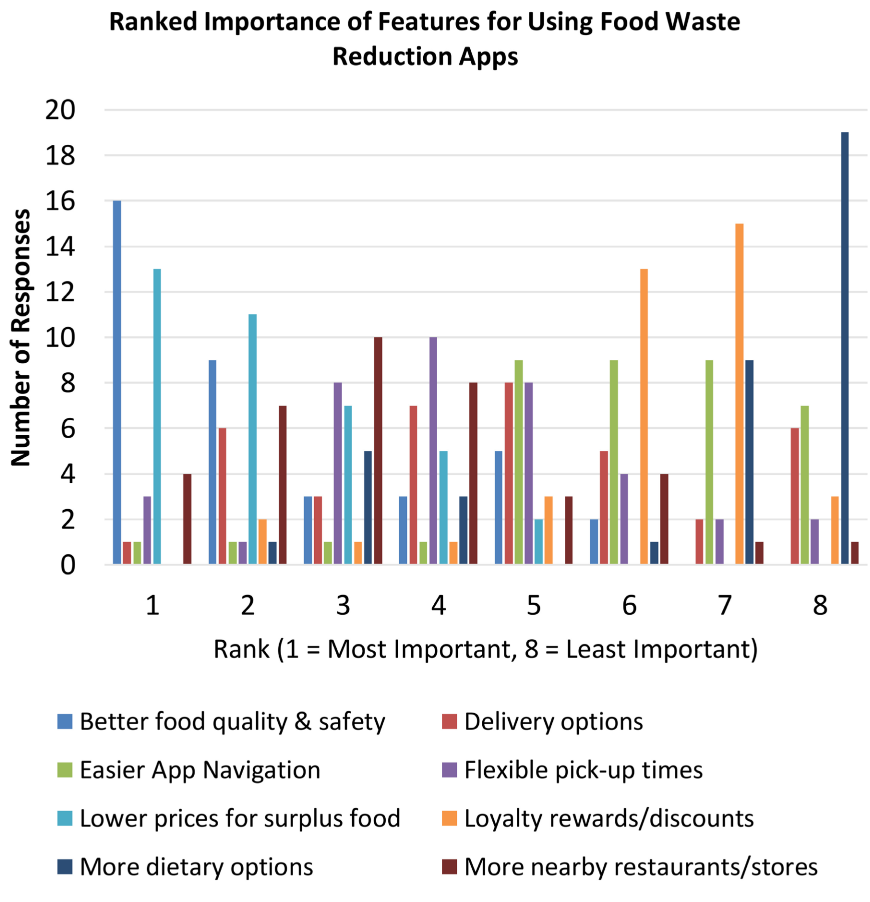

Figure 11. Users rank features of the application.

Once we turn our attention to least important features, we can focus on grouping those answers by combining ranks 7 and 8 and showcasing the total number of responses by feature for just these ranks. This creates a much clearer picture (Figure 12) on features and work streams that should definitely not be included in the immediate road map of the application development.

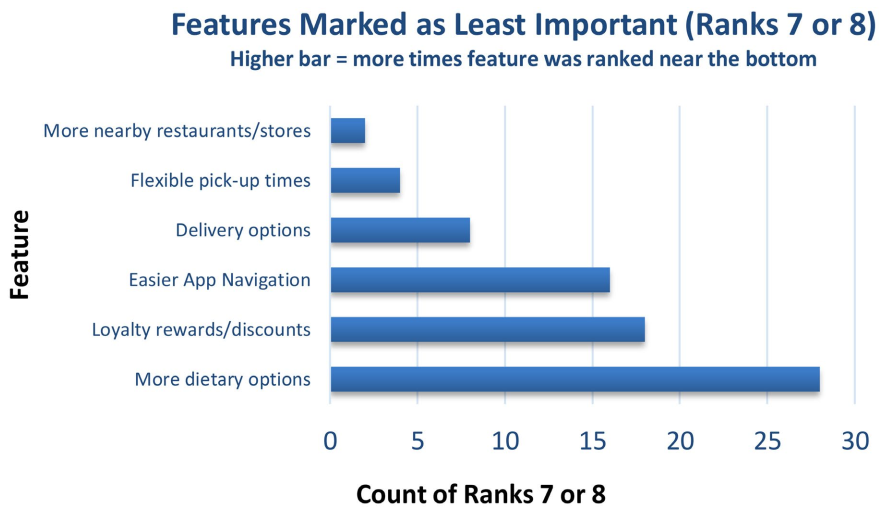

Figure 12. Examining the least desired proposed features of the application.

4.3.3. Implications for Launch Strategy

These insights indicate that while dietary accommodations and loyalty programs might bolster long-term user retention or niche markets, they should not form the core message for an initial app launch. By dedicating development resources and marketing efforts to the elements users clearly prioritize—such as significant cost savings and clean, intuitive user experiences—the app is more likely to attract and retain a broader audience. As user engagement grows, the platform can later introduce or refine the lower-ranked features, aligning them more precisely with user feedback and emerging trends. This data-driven prioritization ensures that early development efforts match the true needs and preferences of potential users, ultimately improving the prospects for a successful rollout.

4.4. Barriers

4.4.1. Cost and Discount Expectations

Data from the expected discount (discount_expected variable) indicates that many participants desire substantial price reductions on surplus food—40% or more—in order to feel incentivized to make purchases through food waste reduction apps (Figure 13). A sizable subset of respondents even indicated that they would be interested only if discounts reached 80% or higher, suggesting a distinct cost sensitivity among users. This finding implies that relatively modest markdowns (25% or less) may not be compelling enough to overcome the behavioral inertia of relying on conventional grocery shopping habits. From a policy and design standpoint, developers may need to negotiate deeper price cuts with partner businesses or offer loyalty rewards to address this strong consumer preference for significant discounts. Otherwise, the perceived savings may not offset doubts about food quality or the extra step of using a specialized app, ultimately hindering widespread adoption.

Figure 13. Overall interest in trying the app.

4.4.2. Usability, Trust, and Perceived Impact

Beyond cost considerations, the code variables ui_preference and app_can_make_impact highlight additional barriers. Participants ranking "Easier App Navigation" and "Better Food Quality & Safety" at high levels indicate ongoing concerns about usability and trust in leftover or surplus food. Even among those who believe surplus food sales can reduce waste overall, skepticism arises if the interface is unclear or if the condition of discounted items seems uncertain. In parallel, some respondents are not fully convinced that the platform is actually reducing waste—despite stating that an app could make a difference, their confidence in its current impact appears more guarded. This discrepancy implies that transparency in sourcing, clear labeling of food quality standards, and user-friendly design elements (e.g., simplified menus, prominent trust indicators) might be pivotal in shifting perceptions and moving occasional or hesitant users toward more consistent app usage.

Understanding consumer attitudes toward food waste reduction requires effective survey methodologies. Ahmed, S., Stewart, A., Smith, E., Warne, T., & Byker Shanks, C. (2021), a team of food sustainability researchers, conducted a large-scale online survey examining consumer perceptions, behaviors, and knowledge of food waste in Montana, USA. Their study used a self-administered electronic survey distributed via social media platforms to reach a broad audience. The study highlights the advantages of digital survey distribution, including cost-effectiveness and wide accessibility. However, they also acknowledge key challenges, such as self-reporting biases—where respondents may underestimate their food waste due to social desirability bias. To improve accuracy, they recommend incorporating behavioral tracking methods, such as app-based waste logging or purchase history analysis, which could be integrated into existing and future platforms designed to combat food waste.

5. Discussion & Limitations

This study provides initial evidence that environmental concern is the chief driver of stated intent to try a surplus-food app, whereas cost savings and food-safety worry did not reach significance in a sample of thirty-eight respondents. The following limitations temper these conclusions and guide future work.

Social-desirability bias. Although the survey was anonymous, respondents may have overstated pro-environmental attitudes and understated skepticism to appear socially responsible. Future studies should add an embedded lie-scale or indirect questioning to detect this bias.

Self-report versus behavior. Intentions and self-reported app use were not verified against actual purchase logs, so reported adoption may exceed real uptake. Partnering with an app provider would allow linkage of questionnaire responses to in-app transactions and thereby strengthen causal inference.

Sample size and power. With {N} = 38, the study was powered to detect only large effects; non-significant predictors (e.g., cost savings, food-safety concern) might reach significance in a larger, more diverse panel. Replication with a stratified online panel is therefore essential.

Future research agenda. A practical next step is to increase sample size and to link baseline survey responses to anonymized in-app activity logs (e.g., downloads, redemptions, session counts). Tracking real behavior over time will show which stated motivations translate into use and which barriers still suppress engagement.

6. Conclusion

This study investigated consumer behavior around food waste reduction apps, particularly Too Good To Go, by gathering input from current users, potential users, and non-users. We deployed an online survey that combined quantitative and qualitative elements to capture both general trends and individual perspectives. Although these methods provided rich insights into user motivations, attitudes, and barriers, our survey-based approach inherently carries limitations—such as social desirability bias and uneven sample representation—which should be considered when generalizing the findings.

Overall, we found that cost savings, environmental awareness, and convenience influence initial app adoption, while concerns over usability and surplus food quality can reduce engagement. The finding that environmental concern—but not cost savings—predicts adoption intent suggests marketing messages should highlight the climate-impact angle rather than price alone. The non-significant, negative coefficient for food-safety concern signals a potential barrier that merits further study with a larger sample.

Participants highlighted the value of targeted marketing campaigns, partnerships with local businesses, and clear communication about food freshness to maintain ongoing usage. Looking ahead, gathering more robust long-term data and conducting cross-regional comparisons could deepen our understanding of cultural differences and track how repeated use impacts household food waste. Longitudinal studies (which follow the same participants over time) may clarify the evolution of user retention, while randomized pilot programs can refine local outreach strategies. Exploring gamification features might also encourage sustained engagement.

In conclusion, the findings confirm that these platforms can effectively reduce food waste when they align with user needs, especially around affordability and ease of use. Establishing strong collaborations with businesses, tailoring promotions to specific demographics, and offering transparent information on food quality can increase adoption and retention. By prioritizing these fundamentals, developers can create a strong user base, ultimately leading to broader environmental impact and more sustainable consumer practices.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A: Data Cleaning

A.1. Survey Completion and Progress Checks

Prior to any analysis, the data set was pruned to exclude responses deemed invalid due to incomplete progress. Specifically, a minimum progress threshold required that respondents achieve a 100% completion rate, ensuring that partially finished or abandoned surveys were excluded. In tandem, only surveys marked "Finished == TRUE" were retained, serving as a secondary check to confirm that participants had finalized and submitted their responses.

A.2. Response Duration Criteria

To safeguard against individuals rushing through the questionnaire or lingering excessively (thus potentially invalidating their responses), the script evaluated completion times (duration_seconds) and filtered out extreme outliers. This process involved computing the mean and standard deviation of completion times, retaining only those responses whose durations fell within ±3 standard deviations of the mean. By applying this criterion, the study limited the influence of rapid-click or abnormally delayed submissions that might otherwise skew the data.

Recognizing the importance of contextual data, the cleaning phase also removed any rows that lacked critical demographic fields—including age, household_income, education_level, and location. If a given response had missing values in all of these core variables, it was considered too incomplete to provide meaningful insights or segment-specific conclusions.

An attention check item was embedded in the survey as an additional quality control measure. Respondents were expected to select "Strongly Agree" for this particular statement to verify attentiveness. Responses that did not fulfill this requirement, or that contained missing values in the attention check field, were removed. By enforcing this rule, the dataset was further refined to preserve only respondents who provided thoughtful, engaged answers.

A.3. Importance of a Bell-Curve Distribution

Observing an approximate bell-curve distribution in demographic metrics—such as age—is often desirable in consumer research, as it suggests a representative spread of participants rather than an overconcentration in one age bracket (**Figure A1**). When the distribution skews heavily to younger or older cohorts, inferences about consumer behavior may be less generalizable. While genuine populations may not always reflect a perfect bell curve, an approximately normal distribution allows for the use of a broad set of standard statistical techniques (e.g., certain hypothesis tests and confidence intervals) that assume normally distributed data. Consequently, this increases the reliability of subsequent insights regarding user adoption and engagement, ensuring the study can draw robust conclusions about how different segments of the population perceive or interact with a food waste reduction application.

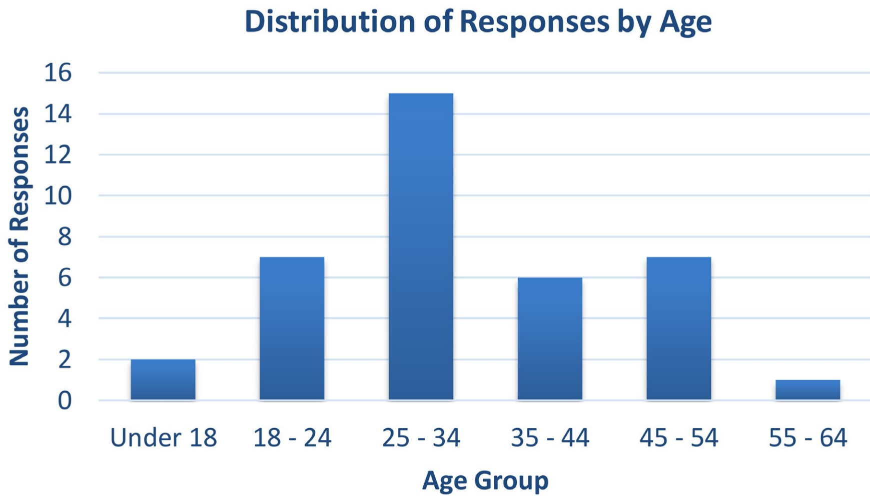

Figure A1. Bell-curve distribution in demographics.

Online Appendix B: R Scripts & Technical Notes

The appendix is available online at the following URL:
https://docs.google.com/document/d/1QurnVQJ85eINegkFKAKe-4UunLU6HEOQwreOcu8VKWg/edit?usp=sharing