Consumer preferences for sustainable food packaging: A joint analysis of random utility maximization and random regret minimization

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Abstract: The pollution caused by conventional plastic food packaging can pose a significant environmental challenge. Our study uses a discrete choice experiment to examine consumer preferences for various types of sustainable milk packaging. To reveal the behavioral mechanisms involved in decisions regarding sustainable

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packaging, we incorporate two behavioral choice frameworks: random utility maximization and random regret minimization. The results indicate that consumer preferences vary with the different behavioral frameworks, demonstrating significant heterogeneity in consumer tastes. Furthermore, consumer preferences for sustainable packaging are influenced by their purchase frequency, trust, and conservation awareness. Our findings support food industry's sustainable transition and packaging adoption.

Keywords: sustainable packaging, discrete choice experiment, random utility maximization, random regret minimization

JEL Codes: C25; Q53

1. Introduction

The pollution caused by conventional plastic packaging not only results in irreversible damage to the ecological environment but also poses risks to the health of both animals and humans (Li et al., 2016; Smith et al., 2018). Between 1950 and 2015, global plastic production grew at an average compounded annual rate of 8.4% (Thompson, 2017), with total plastic stocks reaching 8.3 billion tons (Geyer et al., 2017). The packaging industry accounts for the largest share of plastic demand, which is around 40% (Plastics Europe, 2020), while recycling rates have remained below 10% (Geyer et al., 2017). The plastic packaging that escapes recycling systems often enters ecosystems, posing environmental and health hazards.

Governments worldwide have been formulating strategies to mitigate plastic packaging pollution, but the outcomes have been limited. For example, the city of San Francisco implemented a ban on the sale of bottled water to encourage consumers to switch to tap water. However, this strategy was ultimately ineffectively implemented (Timm, 2014). Similarly, France introduced recycling fees in 2010 to discourage plastic usage, but plastic consumption did not decline (Orset et al., 2017). Overall, bans on plastic use have not successfully addressed the issues of plastic consumption and recycling (Van Asselt et al., 2022). Therefore, it is essential to develop sustainable strategies in the plastic packaging industry to alleviate pollution caused by plastic waste.

Currently, much of the disposable food packaging is made from Polyethylene Terephthalate (PET) (Orset et al., 2017), which is commonly used for beverage bottles, food containers, and takeout packaging. PET packaging is a major contributor to environmental pollution. In response, the food industry has developed several sustainable packaging alternatives, including Biodegradable Plastic (PLA), Tetra Pak (TP), and Polyvinyl Alcohol (PVA). Previous studies have focused on consumer preferences for PET packaging versus a single alternative sustainable option. The contribution of this study is that we jointly consider PET packaging along with three types of sustainable packaging, namely PLA, TP, and PVA. We empirically analyze consumer preferences and willingness to pay (WTP) for these sustainable packaging options. Additionally, we explore the heterogeneity in consumer preferences, contributing to the literature on ecological economics and the circular economy aimed at mitigating plastic packaging pollution.

Our study focuses on regular room-temperature boxed plain milk for the following three reasons. First, milk is a staple food product in China and is a typical packaged food item with high production and consumption volumes (Cheng et al., 2015; Yin et al., 2018). Second, due to the perishable nature of milk, its packaging is a product feature that concerns both producers and consumers. Third, milk packaging in China exhibits high diversity and functionality, allowing us to include PET, PLA, TP, and PVA as four packaging options in our research (Meneses et al., 2012; Karaman et al., 2015).

The discrete choice experiment (DCE) is widely used in research on consumer behavior. For example, Wensing et al. (2020) employed a DCE to analyze the impact of various sustainable nudging strategies on consumer preferences for PLA packaging. Similarly, Van Asselt et al. (2022) used a DCE to explore consumer preferences for eco-labels. These studies are based on the framework of random utility maximization

(RUM), which assumes that consumers are fully rational and seek to maximize utility through their choices. However, Simon (1955) questioned the assumption of fully rational decision-making, arguing that consumers have limited cognitive abilities and are influenced by bounded rationality when making choices. Following this, Bell (1982) proposed regret theory, which suggests that decision-makers are only boundedly rational and tend to make choices that minimize expected regret. Later, Chorus (2010) introduced the random regret minimization (RRM) framework, where regret arises when a forgone option is superior to the chosen option in one or more attributes (Loomes and Sugden, 1982). The basic assumption of the RRM model is that individuals act to minimize anticipated regret. Previous literature indicates that the RRM model has been applied in fields such as transportation (Chorus et al., 2008), psychology (Zeelenberg et al., 2007), and health (Boeri et al., 2013), though its application in understanding consumer food behavior remains limited.

Thus, the second contribution of this study is that, through the application of a DCE, we suggest that when consumers make food-related choices, they may be influenced not only by utility maximization but also by the degree of anticipated regret associated with their choices. Therefore, we introduce the RRM model into the study of consumer preferences for food packaging, distinguishing our research from previous studies that only considered the RUM model. We compare the differences between the two decision-making frameworks and by using a flexible econometric framework further allow them to coexist in the analysis without pre-defining which mode a consumer adopts. This expands the application of such methods in consumer behavior research.

Additionally, we find that besides price, consumers may consider other characteristics when choosing packaged food, such as the number of days remaining on the date label on the day of purchase and shelf life (Wilson et al., 2017; Li et al., 2025). We incorporate these attributes into our DCE. Moreover, previous literature indicates that factors such as consumer purchasing frequency, trust, and conservation awareness can influence their behavior (Bronnmann et al., 2021; Van Asselt et al., 2022; Li et al., 2024). Based on this, we include consumer characteristics under both the RUM and RRM frameworks, providing new insights into consumer preferences for sustainable packaging and the role of heterogeneity within different decision-making frameworks.

Our findings reveal that differences in decision-making frameworks lead to changes in consumer preferences. Under both the RUM and RRM frameworks, consumers tend to prefer purchasing milk in PLA packaging. Consumers under the RRM framework also show interest in purchasing TP packaging and are willing to pay a higher premium for both PLA and TP packaging. Furthermore, our results indicate that over 60% of the sample followed the RRM decision-making rule. Consumer preferences for sustainable packaging are also influenced by purchase frequency, consumer trust, and conservation awareness. Our conclusions provide evidence to support the sustainable transition of the food industry and the adoption of sustainable packaging. The findings also offer new insights for policymakers and researchers to better understand and guide consumer behavior.

The remainder of this study is structured as follows: Section 2 reviews the relevant literature, Section 3 outlines research materials and methods, Section 4 presents the formulation of the RUM and RRM models and consumer WTP, Section 5 discusses the empirical results of the DCE, and Section 6 provides conclusions and implications.

2. Literature Review

Plastic Pollution and Sustainable Packaging

Polyethylene Terephthalate (PET) is one of the most widely used commodity polymers, particularly prevalent in food packaging (Mantia et al., 2012). It is primarily derived from non-renewable petroleum and natural gas and its production process emits substantial amounts of greenhouse gases (Álvarez-Chávez et al., 2012; Philp et al., 2013). While PET usage has grown significantly over the past several decades, it has also raised considerable concerns regarding its environmental and health impacts.

Consumers' understanding of sustainability is closely linked to the materials used in packaging, with "sustainable" often signifying biodegradability, reusability, or recyclability (Herbes et al., 2018; Kale et al., 2007). Currently, three primary types of sustainable packaging have been developed as potential replacements for PET: Polylactic Acid (PLA), Tetra Pak (TP), and Polyvinyl Alcohol (PVA).

PLA is a biodegradable polymer that can be used in food packaging and has a similar appearance to conventional PET food storage packaging (Mantia et al., 2012). It is primarily derived from renewable resources such as plant-based materials like corn. PLA offers certain sustainability advantages over PET, as its production process can reduce greenhouse gas emissions by 14% –20% (Álvarez-Chávez et al., 2012; Philp et al., 2013). The market value of PLA packaging is estimated to reach $260 million

(Mahalik and Nambiar, 2010). TP is a form of paper-based packaging that consists of materials such as cardboard, polyethylene, and aluminum foil (China News, 2010). PVA is non-toxic, non-irritating to human skin, and can be used to produce transparent films for food and beverage storage or packaging (Faber et al., 2005).

Growing environmental awareness and supportive policy initiatives, such as the European Commission’s promotion of bio-based and recyclable materials (European Commission, 2015; 2018), have accelerated interest in these alternatives. For instance, the introduction of PLA-based packaging in Italy’s bottled water market demonstrated consumers’ willingness to pay a premium for more sustainable packaging options (De Marchi et al., 2020).

In the early stages of packaging technology development, extensive literature has explored consumer preferences for alternative packaging materials. For instance, Xie et al. (2011) compared consumer preferences for PET packaging versus aluminum packaging, while Acuff and Kaffine (2013) and Fernqvist et al. (2015) focused on PET versus paper-based packaging. Klainman et al. (2016) expanded on these studies by including more packaging materials and evaluating consumer WTP for plastic, glass, cardboard, and aluminum packaging. Their findings indicated that consumers were willing to pay a premium for recyclable plastic packaging, driven by the perception that traditional plastics are non-recyclable and harmful to the environment.

Yano et al. (2014) examined the environmental benefits of PLA packaging, finding that compared to PET packaging, PLA could reduce greenhouse gas emissions by 14% to 20% (European Commission, 2015; 2018). Petkosha et al. (2021) argued that sustainable and biodegradable materials like PLA not only help alleviate environmental pollution but also enhance food safety and quality. Orset et al. (2017) compared PLA packaging with various PET packaging options and found that consumers were willing to pay more for PLA packaging when provided with information about its environmental benefits. Friedrich (2020) compared PLA, PET, cardboard/wood, and aluminum packaging, reaching conclusions similar to Orset et al. (2017).

In summary, previous literature has primarily focused on consumer preferences for a single type of sustainable packaging, such as PLA, without systematically comparing how consumers evaluate and accept different sustainable packaging alternatives. This study contributes to the literature by providing a comprehensive assessment of consumer preferences across multiple sustainable packaging solutions, offering broader insights into substitution potential, market segmentation, and the relative appeal of various sustainability strategies in packaging design.

Random Regret Minimization

The RUM framework is a widely used decision-making model in economics and behavioral science (Hess et al., 2018). It assumes that individuals act fully rationally to maximize utility when making choices. However, behavioral economics and psychology have shown systematic deviations from full rationality (Simon, 1955; Kahneman and Tversky, 1979). Based on this, scholars suggest incorporating the "regret" factor in the RRM framework, in which consumers seek to minimize regret rather than maximize utility (Chorus, 2010).

The RRM model has been applied to understand consumer behavior related to travel modes (Chorus et al., 2008; van Cranenburgh et al., 2015), environmental decisions (Zhang et al., 2021), lifestyle choices (Boeri et al., 2013), and tourism demand (Thiene et al., 2012). Biondi et al. (2019) were the first to apply the RRM models to analyze consumer preferences in the food domain. Their results showed that the goodness-of-fit and predictive accuracy of the RUM and RRM models were similar. However, Piracci et al. (2023) found differences between the RUM and RRM model outcomes in a study on consumer preferences among PET plastic packaging, no packaging, and bioplastic packaging for tomatoes. This suggests that consumer decision-making may not always follow either the RUM or the RRM framework exclusively, indicating potential heterogeneity in decision-making behavior. Based on this, we incorporate the RRM model into our study, examining the heterogeneity of consumer choices for sustainable packaging under both the RUM and RRM frameworks. This expands the application of the RRM model in the field of consumer food choices.

Additional Attributes in Discrete Choice Experiments and Consumer Characteristics

Although many consumers are aware that the packaging of the products they purchase affects the ecological environment, this awareness does not necessarily translate into choosing the most sustainable packaging (Martinho et al., 2015; Chakori et al., 2021). Consumers may make choices based on other food attributes. Wilson et al. (2017) and Chakori et al. (2021) found that the number of days remaining on the date label on the day of purchase is a critical attribute influencing consumer decisions regarding packaged food. Li et al. (2025) demonstrated that consumers prioritize shelf life in their purchasing behavior. Coibion et al. (2021) and Calvo-Porral et al. (2016) found that purchasing frequency regulates consumer familiarity with specific products, making it a key variable associated with consumer purchasing behavior. The level of trust that consumers have in food manufacturers depends on whether they believe these entities follow established rules and food safety laws (Bargain and Aminjonov, 2020). The higher the trust in food manufacturers in general, the more likely consumers are to increase their consumption (Li et al., 2024). Attitudes toward the environment and conservation may also be a significant determinant of sustainable purchasing decisions (Grunert et al., 2014; Martinho et al., 2015). Van Asselt et al. (2022) found that stronger environmental and conservation awareness among consumers is associated with a reduction in PET packaging purchases. Therefore, our study considers the effects of these factors related to product and consumer characteristics.

3. Research Materials and Methods

Discrete Choice Experiment Design

We surveyed Chinese food consumers through an online questionnaire. Before the formal sample collection, five rounds of pretests were conducted to refine the survey process and improve language clarity. The first section of the questionnaire included questions related to consumer habits, consumer trust, and waste management practices concerning packaged milk. The second section involved a DCE that included different types of milk packaging. The final section gathered consumer demographic and socio-economic information. Following Penn et al. (2019), two trap questions were embedded in the questionnaire to assess respondent attentiveness. Any respondent who failed either question was excluded from further analysis.

In the first section of the survey, referring to Piracci et al. (2023), questions on consumer habits asked respondents about the frequency of household consumption of packaged milk during the last month. Consumer trust was measured on a seven-point Likert scale (1 = "strongly agree", 7 = "strongly disagree") to assess manufacturers' ability to ensure the safety and quality of food they produce (Mazzocchi et al., 2008; Li et al., 2025). Conservation awareness was measured on a three-point Likert scale (1 = "reduce food waste", 2 = "no significant change", and 3 = "increase food waste") to capture respondents' beliefs regarding whether composting strategies can help mitigate food waste (Qi and Roe, 2017; Li et al., 2024).

In the second section of the survey, we employed Stata 16.0 to conduct a D-efficient design for the DCE. The design generated a total of 15 choice sets, which were evenly divided into three blocks, with each block containing five choice sets. Respondents were randomly assigned to one of the blocks. We employed an unlabeled design where the labels of options in each choice set were placeholders instead of the name of a specific product. Each choice set presented four options: A, B, C, and D. Options A, B, and C were milk options with varying product features, while Option D was a "no purchase" option. Respondents were instructed to choose only one option per choice set. We selected the most common packaging size found in the Chinese market, specifically 16-box cartons of room-temperature milk, with each box containing 180 ml. Before the DCE, respondents were shown a "cheap talk" script (Penn et al., 2019) and a detailed explanation of the different packaging materials. Afterward, respondents completed five choice sets. A certainty question followed each choice set to gauge respondents' level of certainty about the choices they just indicated (Craig, 2014; Penn and Hu, 2023).

Attribute Design

Appendix Table A1 presents the attributes and their levels used in the DCE. The four packaging materials were PLA, TP, PVA, and PET. They reflected the materials of the 16 individual inner boxes within the milk carton, not the outer carton itself. In China, TP and PVA are widely recognized sustainable packaging materials, commonly referred to by their acronyms (Georgiopoulou et al., 2021; Settier-Ramírez et al., 2020; Rehim et al., 2023; Dong et al., 2024). Many milk producers also display sustainability logos when using TP or PVA, which further reinforces consumer familiarity. In contrast, PLA is relatively new to the market. Because of this, additional explanations about PLA were provided in our survey.

After summarizing the sales prices of packaged milk in the Chinese market, and controlling for packaging size, we used four levels covering a range incorporating two standard deviations on each side of the mean to set the levels of purchase price in this study. The final price levels were RMB 29.8, RMB 52.8, RMB 75.7, and RMB 98.7 for the 2880ml carton of milk considered. Additionally, considering the characteristics of packaged milk in the Chinese retail market, for the number of days remaining on the date label on the day of purchase, we included six levels: 30 remaining days, 24 remaining days, 18 remaining days, 12 remaining days, 6 remaining days, and 0 remaining day. The shelf life attribute included two levels, 120 days and 30 days, respectively.

In China, food date labels include the production date and the shelf life, indicating the period during which the food maintains its guaranteed quality. For example, a label might say "produced on October 1, 2025" with "quality assured for 90 days". The shelf life, or the number of days after production, is directly visible to consumers. To determine the remaining days of assured quality, consumers first calculate the "terminal date" by adding the shelf life to the production date, similar to the system used in the U.S. They then subtract the purchase date from the terminal date to find the number of remaining days (Li et al., 2025).

Data Collection

The final sample was collected through a major first-party professional Chinese market research firm called "Lediaocha", which conducted the survey online. Formal sample collection began in September 2021 and was completed by the end of October 2021. The sample was stratified based on population proportions from China's Seventh National Census, with respondents distributed across provinces/provincial level metropolitans or autonomous regions. After excluding incomplete responses and those that failed the attention checks, a total of 612 valid questionnaires were retained for this study.

4. Econometric Analysis

Random Utility Maximization and Random Regret Minimization Model

When choosing among sustainable packaging options, consumers either maximize their utility or minimize their regret, corresponding to the frameworks of random utility maximization (RUM) or random regret minimization (RRM), respectively. To analyze our DCE, we start with the conditional logit (CL) model in RUM (RUM-CL), based on the utility function outlined in Marschak (1960):

$$U_{njt} = V_{njt} + \varepsilon_{njt} = \beta' X_{njt} + \varepsilon_{njt} \quad [1]$$

where U_{njt} is the utility of consume n choosing alternative j in choice set t, V_{njt} represents the deterministic utility, ε_{njt} is the error term, X is a vector of attributes related to the DCE, and β is the vector of unknown parameters to be estimated.

Following McFadden (1974), assuming that the error component is independently and identically distributed as a maximum extreme value type I, the probability that consumer n selects alternative j in choice set t follows the RUM-CL specification:

$$P_{njt}^{RUM} = \frac{e^{V_{njt}}}{\sum_{k=1}^{K} e^{V_{nkt}}} \quad [2]$$

According to Manski (1977), Loomes and Sugden (1982), and Chorus et al. (2008), the RRM model is defined as individuals make choices to avoid situations in which the unchosen option would ultimately appear more attractive in some of the attributes, as such outcomes would generate regret. Therefore, it assumes that individuals minimize expected regret when choosing alternatives, rather than maximizing utility. The regret minimization function can be written as:

$$RR_{njt} = R_{njt} + \theta_{njt} = \delta' T_{njt} + \theta_{njt} \quad [3]$$

where the overall regret RR_{njt} consists of observable regret R_{njt} and an unobservable error term θ_{njt}, T is a vector of attributes related to the DCE, and δ represents the vector of unknown parameters to be estimated.

$$R_{njt} = \sum_{k\neq j}^{K}\sum_{m=1}^{M} R_{j\leftrightarrow k,m} = \sum_{k\neq j}^{K}\sum_{m=1}^{M} ln\ [1 + exp\{\delta_m * (x_{km} - x_{jm})\}] \quad [4]$$

Each alternative is described by a set of attributes M (referred to as m), where $R_{j\leftrightarrow k,m}$ represents the pairwise comparison of regret between alternative k and alternative j for attribute m. $\sum_{k\neq j} R_{j\leftrightarrow k,m}$ is comparable to $\beta' X_{njt}$ in the RUM model, but instead of mapping attribute levels to utility, the RRM framework maps them to regret.

Assuming that the negative of the error component is independently and identically distributed as a maximum extreme value type I, minimizing the random regret is mathematically equivalent to maximizing its negative. The choice probability under the classical RRM model (RRM-CL) is：

$$P_{njt}^{RRM} = \frac{e^{(-R_{njt})}}{\sum_{k=1}^{K} e^{(-R_{nkt})}} \quad [5]$$

van Cranenburgh et al. (2015) extended the classical RRM model by introducing the scale parameter μ. We refer to this as the μRRM model, where the relationship between the scale parameter and error variance is $var(\theta) = (\pi^2\mu^2/6)$. In this model, the regret function is defined as $R_{j\leftrightarrow k,m} = ln\ [1 + exp\ \{(\delta_m/\mu)(x_{km} - x_{jm})\}]$.

The model setup of the μRRM model is similar to that of the classical RRM model, with the key difference being that μ determines the shape of the regret function, which reflects the depth of regret. Specifically, μ represents the degree of aversion to regret in decision-making. It provides insights into how much a decision is driven by the relative importance of losses (regret) between the alternatives. Given the taste parameter δ_m divided by the scale parameter μ, as the value of μ increases, the ratio δ_m/μ decreases, which in turn means that the extent of regret becomes smaller. Conversely, the extent of regret becomes larger.

The choice probability under the μRRM model (μRRM-CL) is:

$$P_{njt}^{\mu RRM} = \frac{e^{\mu(-R_{njt})}}{\sum_{k=1}^{K} e^{\mu(-R_{nkt})}} \qquad [6]$$

Unobserved Preference Heterogeneity

The classic RUM-CL model assumes that all elements of the preference parameter vector β are constant across all individuals, and that the error terms ε_{njt} are independently and identically distributed across all individuals and alternatives. To further control respondents' unobserved preference heterogeneity, we introduce the mixed logit (ML) model. Developed by Train (2009), the ML model allows preference parameters to follow specified distributions, thereby relaxing the restrictive assumptions of the CL model (McFadden and Train, 2000). Based on RUM, the utility function for the ML model can be expressed as:

$$U_{njt} = \beta_n' X_{njt} + \varepsilon_{njt} \qquad [7]$$

where the vector of random parameters β' are individual specific. The choice probability under the mixed logit RUM (RUM-ML) model is:

$$P_{njt}^{RUM} = \int \frac{e^{V_{njt}(\beta_n')}}{\sum_{k=1}^{K} e^{V_{nkt}(\beta_n')}} f(\beta) d\beta \qquad [8]$$

Following from this, a natural extension is to apply the ML framework to the RRM model, allowing for a more structured comparison with the RUM-ML model. In both RUM and RRM models, the taste parameters are assumed to follow a normal distribution, while price is considered fixed. The regret function is similar to equation [7], and the choice probability under the mixed logit RRM (RRM-ML) model is:

$$P_{njt}^{RRM} = \frac{e^{(-R_{njt}(\delta_n'))}}{\sum_{k=1}^{K} e^{(-R_{nkt}(\delta_n'))}} f(\delta) d\delta \quad [9]$$

Hybrid RUM-RRM Model

Most studies exploring RUM and RRM models focus on which framework provides a better fit for a given dataset. All these studies are established on the assumption that all surveyed respondents are either utility maximizers or regret minimizers. However, a sample may represent a mixture of both. Boeri and Longo (2017) proposed that some behaviors can be better explained by the RUM model, while other types are better captured by the RRM model, leading to the development of the hybrid RUM-RRM model. To better distinguish these two types of decision makers, following Hess et al. (2012) and Boeri et al. (2014), a two-class latent class (LC) model can be used, where one class captures RUM decision-makers and the other represents RRM decision-makers. The LC model can be regarded as a semi-parametric version of a mixed model, in which heterogeneity is represented by c discrete mass points, with c denoting the number of classes. The choice probability for individual n belonging to class c under the hybrid RUM-RRM model is given by:

$$P_{njt} = \pi_{nc} P_{njt}^{RUM} + (1 - \pi_{nc}) P_{njt}^{RRM} \quad [10]$$

where the membership probability π_{nc} for the RUM class is typically a logit model.

$$\pi_{nc} = \frac{exp\ (\gamma_c + Z_c' \varphi_n)}{exp(\gamma_c + Z_c{}'\ \varphi_n) + 1} \quad [11]$$

where γ_c is class-specific constant, φ_n denotes personal characteristics that influence individual choices, and Z_c' is a vector of class-membership parameters.

Willingness to Pay

According to Train (2009), in the RUM-CL and RUM-ML models, consumer WTP for the kth attribute is the negative ratio of the coefficient of the kth attribute m to the coefficient of price:

$$WTP_m^{RUM} = -\beta_m/\beta_{price} \quad [12]$$

According to Chorus et al. (2013), WTP in the RRM-CL and RRM-ML models can be expressed as:

$$WTP_m^{RRM} = -\frac{\sum_{k\neq j}\left[\frac{-\delta_m}{1+\frac{1}{\exp\left[\delta_m\left(x_{km}-x_{jm}\right)\right]}}\right]}{\sum_{k\neq j}\left[\frac{-\delta_{price}}{1+\frac{1}{\exp\left[\delta_{price}\left(x_{km}-x_{jm}\right)\right]}}\right]} = -\frac{\delta_m}{\delta_{price}} * \frac{\sum_{k\neq j}\left[\frac{\exp\left[\delta_m\left(x_{km}-x_{jm}\right)\right]}{1+\exp\left[\delta_m\left(x_{km}-x_{jm}\right)\right]}\right]}{\sum_{k\neq j}\left[\frac{\exp\left[\delta_{price}\left(x_{km}-x_{jm}\right)\right]}{1+\exp\left[\delta_{price}\left(x_{km}-x_{jm}\right)\right]}\right]} \quad [13]$$

We estimate all CL and ML models, as well as the WTP values using Stata 16.0 (Gutiérrez-Vargas et al., 2021; Zhu et al., 2024), while fitting the hybrid RUM-RRM model through Biogeme (Bierlaire, 2003).

5. Results

Descriptive Statistics

Table 1 presents the descriptive statistics of the dependent variable, independent variables, and demographic information. In our sample, the average household purchases milk approximately 4.8 times per month. Respondents showed a neutral level of trust in food manufacturers. Around half of the respondents believed that composting strategies for waste disposal could mitigate food waste. The average age of the sample is about 33 years, with 55.4% of respondents being married. The average education level is a college degree, and the average household size is around three members, with an average of 0.8 children under the age of 18 and 0.3 elderly members over the age of 60. While our sample is generally younger and better educated compared to the national average[1], this trend is expected and consistent with typical online survey studies (Xiong et al., 2024).

<<Table 1 about here>>

Discrete Choice Experiment Results

Table 2 reports the results of three CL model specifications: the RUM-CL, RRM-CL, and μRRM-CL models. Based on the log-likelihood values, the RRM model provides a better fit for our data. The significance of parameters across the three models is highly consistent. We focus on the three parameters related to packaging: *PLA, TP,* and *PVA.*

In the RUM-CL model, the *PLA* parameter is positively significant at the 1% level, while the *TP* and *PVA* parameters are not significant, indicating that only the PLA packaging increases consumer utility compared to PET packaging. The *Price* parameter is negatively significant at the 1% level, indicating that utility decreases as prices increase. Furthermore, the *Date* parameter is positively significant at the 1% level, and the *Shelflife* parameter is negatively significant at the 1% level, suggesting that consumers prefer products with more days remaining on the date label but shorter shelf lives. This result is consistent with our expectation, as Wilson et al. (2017) found that consumers are willing to pay higher premium for food with a shorter shelf life, and Chinese consumers typically associate longer remaining days or shorter shelf life with fresher and better quality (Li et al., 2025).

The results from the RRM-CL and μRRM-CL models demonstrate the potential contribution of regret minimization in decision-making. The scale parameter μ is negatively significant, indicating that the μRRM-CL model captures more information than the RRM-CL model. The *PLA* parameter remains positively significant at the 1% level, suggesting that not choosing the PLA packaging induces higher anticipated regret compared to not choosing the PET packaging. The *Price* parameter is negatively significant at the 1% level, implying that regret decreases as the non-considered alternative becomes more expensive than the selected one. Additionally, the *Date* and *Shelflife* parameters are also significant at the 1% level. It is worth noting that the *TP* parameter in the RRM-CL model is marginally significant, indicating some differences in parameter significance between the RUM and RRM models. Overall, both the RUM and RRM models indicate that consumers prefer PLA packaging over PET, while decision-making behavior differs between the RUM and RRM frameworks.

<<Table 2 about here>>

We estimate ML models to account for unobserved heterogeneity in consumer preferences. Table 3 reports the results of two ML model specifications: the RUM-ML and RRM-ML models. We specify *Shelflife* and *Optout* as random coefficients. Their standard deviation estimates are significant at the 1% level in both models, indicating that the ML models improve upon the CL models. The log-likelihood values suggest that the RRM-ML model is a better fit for our data. We find that both the RUM-ML and RRM-ML models exhibit the same preference patterns as their corresponding CL models, consistent with the findings of Boeri and Longo (2017) and Mao et al. (2020). Additionally, the *Price* parameter is negatively significant at the 1% level, demonstrating that price is a critical factor in decision-making across both RUM and RRM frameworks. The *Date* and *Shelflife* parameters are also significant at the 1%

level. Differences in decision-making between the RUM and RRM models are also observed in the ML models. The *TP* parameter is positively significant at the 5% level in the RRM-ML model but only marginally significant in the RUM-ML model.

<<Table 3 about here>>

Based on the ML models and applying the delta method, Appendix Table A2 reports the summary statistics for the distributions of the marginal effects of different packaging materials. The results show that the conditional means, standard deviations, maximum, and minimum values of the marginal effects under the RRM model are lower than those of the RUM model, suggesting that the RRM model results are more convergent.

Given that the specification of alternative specific constants (ASCs) may affect parameter estimates in discrete choice models (Rose et al. 2019), we follow the existing literature by including three ASCs in both the CL and ML models, namely *ASC_1*, *ASC_2*, and *ASC_3*, corresponding to alternatives A, B, and C, respectively. The opt-out option (alternative D, "purchase nothing") is treated as the reference alternative (Möser et al. 2019; Demel et al. 2020). Results reported in Appendix Table A3 show that *ASC_1*, *ASC_2*, and *ASC_3* are all positive and statistically significant at the 1% level in the RUM-CL, RRM-CL, and μRRM-CL models, indicating that consumers are more likely to choose product alternatives A, B, or C than the opt-out option. Consistent evidence is obtained from the alternative specification in which the opt-out option is associated with an ASC. As shown in Table 2, the *Optout* parameter is negative and statistically significant at the 1% level across all models, further confirming that consumers, on average, are reluctant to choose the opt-out alternative and instead prefer one of the product alternatives A, B, or C.

These two sets of results are consistent in both direction and economic interpretation, thereby strengthening the internal consistency of the CL model findings. Results reported in Appendix Table A4 further indicate that the RUM-ML and RRM-ML models that account for preference heterogeneity exhibit preference patterns that are fully consistent with those obtained from the corresponding CL models. We further compare the CL and ML estimates obtained under two alternative ASC specifications, namely models with three ASCs and models with a single ASC. Overall, the key parameter estimates are highly robust across specifications. With the exception of minor changes in statistical significance for a small number of parameters, such as *TP*, all remaining coefficients are stable in terms of sign, magnitude, and statistical significance.

To further investigate heterogeneity, we allow for the coexistence of different decision-making processes within the sample by constructing two-class latent class (LC) models incorporating both the RUM and RRM frameworks. Table 4 reports the results of the LC models incorporating RUM-CL and RRM-CL (columns 2 and 3), RUM-CL and μRRM-CL (columns 4 and 5). The parameter μ in Table 4 is not significant, indicating that the combination of RUM-CL and μRRM-CL does not provide additional insights into consumer behavior. Consistent with the CL and ML model results, the *PLA* parameter is positively significant at the 5% level in nearly all models. However, the *TP* and *PVA* parameters are significant in some models. Overall, the results of the two LC models demonstrate robustness. In the LC models, we focus on the membership probability, which reflects the proportion of respondents whose choices are better explained by either the RUM or the RRM processes. The membership probability suggests that depending on the two LC models, about 61.8% to 64.4% of respondents adopted the regret-based choice framework. Our findings show that the utility maximization framework should not be viewed as the sole driver of consumer choices across all decision contexts. Additionally, the class membership coefficients reported in Tables 4 reveal sources of preference heterogeneity. Factors such as *Age, Female, Income, Married, Education, Hsize, Child*, as well as *Elder* all contribute to this heterogeneity.

<<Table 4 about here>>

Willingness to Pay

We further analyze consumer WTP and explore differences in decision-making under the RUM and RRM frameworks. Table 5 reports the WTP estimates for milk packaging under both the RUM and RRM models. We retain the WTP estimates from the μRRM-CL model, as it performs best in Table 2. In addition, we include all ML models, since the RUM-ML outperforms RUM-CL, and RRM-ML further outperforms RUM-ML.

In the μRRM-CL model, consumers are willing to pay a premium of RMB 14.0 per 16-box carton of milk (2880 ml) for PLA packaging, while the premiums for TP and PVA packaging are RMB 5.0 and RMB 4.3 per carton, respectively, though the premiums associated with TP and PVA packaging are not statistically significant. This conclusion holds for the RUM-ML model, whereas in the RRM-ML model the premium for TP (RMB 6.5) is significantly different from zero at the 5% level. These results are consistent with the findings of De Marchi et al. (2020) and Wensing et al. (2020).

On the other hand, in the μRRM-CL model, as well as the RUM-ML and RRM-ML models, the WTP for PLA packaging is estimated to be RMB 14.0, RMB 14.7, and RMB 16.8 per carton, respectively. Given that the market price for a carton of 16 boxes of packaged milk (total 2880 ml) is around RMB 50.0, these premiums represent 28.0% to 33.6% of the market price. The WTP estimates under the RRM framework are slightly higher than those under the RUM framework, though the confidence intervals overlap across these models.

<<Table 5 about here>>

Analysis of Additional Heterogeneity

Tables 6 and 7 report the interaction effects of *Frequency, Trust,* and *Awareness*[2] with packaging materials in the CL and ML models under both the RUM and RRM frameworks. In both tables, the interaction between *PLA* and *Frequency* is significantly positive at the 1% levels, indicating that consumers who frequently purchase a product are more likely to value its sustainable packaging. Similarly, the interaction between *PLA* and *Trust* is positively significant at the 5% and 1% levels, respectively, suggesting that higher trust in manufacturers increases the acceptance of sustainable packaging, leading to a greater purchase intention. Herrmann et al. (2022) also found that consumer trust in companies producing sustainable products directly affects purchasing behavior. Additionally, the interaction between *PLA* and *Awareness* is positively significant at the 1% levels. While Herrmann et al. (2022) suggested that consumers may have doubts about the sustainability of PLA packaging, leading to lower WTP, our results show that consumers with stronger conservation concerns are more inclined to purchase PLA packaged milk. This result holds in both the RUM and RRM models. This contrasts with previous findings, such as those of Boeri and Longo (2017), which indicated that individuals participating in environmental organizations were more likely to follow the utility maximization framework rather than regret minimization.

<<Table 6, 7 about here>>

There are additional factors that may influence consumer preferences for sustainable packaging that were not explored in this study, such as consumer knowledge about sustainable packaging, perceived risk, and regret sensitivity. These aspects present valuable directions for future research.

6. Conclusions and Implications

Our study uses a discrete choice experiment (DCE) to examine consumer preferences for various sustainable milk packaging options under the behavioral frameworks of Random Utility Maximization (RUM) and Random Regret Minimization (RRM). Our primary findings are as follows: first, across both the RUM and RRM models, consumers consistently exhibit a strong preference for purchasing PLA packaging, regardless of the choice model used. This result is also reflected in consumer WTP. Controlling for other factors does not change this finding. Consumers are willing to pay a premium of up to 33.6% for a carton of 16 boxes (2880 ml) of PLA packaged milk compared to the commonly used PET packaging.

Second, decision-making differences exist among consumers based on the varying behavioral frameworks, resulting in changes in the consumer tastes. In the RUM model, consumers predominantly prefer PLA packaging. In contrast, in the RRM model, consumers not only prefer PLA packaging but also exhibit a preference for TP packaging, though their preference and WTP for TP are lower than for PLA. We attribute this difference in preferences to the core distinction between the two decision-making frameworks: while RUM focuses on optimizing utility, RRM emphasizes minimizing regret. When consumers' behavioral frameworks exhibit heterogeneity, these two behavioral frameworks may coexist, as evidenced by our LC model, which shows that more than 60% of the sample follows the RRM decision-making rule. Our findings also highlight the potential application of the LC model to analyze the behavioral decision rules.

Third, our study finds that consumer preferences for sustainable packaging are influenced by purchase frequency, consumer trust, and conservation awareness. PLA packaging, in particular, is highly associated with these three consumer-related variables. Additionally, TP and PVA packaging are also somewhat associated with consumers' conservation awareness.

Our findings offer both practical and policy insights for the development and promotion of sustainable packaging. First, our research supports the idea of promoting sustainable packaging as an alternative to conventional PET plastic packaging. Many food companies, in their sustainability efforts, have primarily focused on post-consumption waste management and recycling solutions, while neglecting the environmental impact of plastic packaging itself. Given that the recycling rate for plastics is only 10%, the effectiveness of these strategies is questionable. Our findings suggest that consumers are willing to accept sustainable packaging and are even willing to pay a premium for it. Studies like van den Oever et al. (2017) show that adopting sustainable packaging does not reduce profit margins for food companies, while Piracci et al. (2023) suggest that offering sustainable packaging can increase profitability. These findings provide evidence that sustainable packaging can aid in the food industry's transition toward sustainability.

Second, marketers should account for the differences in consumer decision-making processes. For consumers who prioritize utility maximization, PLA packaging can be marketed as the preferred option over other sustainable alternatives. Promotional and advertising efforts targeting this group should focus primarily on PLA, potentially reducing overall marketing costs. On the other hand, for consumers inclined toward regret minimization, marketers should emphasize the range of sustainable packaging alternatives (such as PLA, TP, and PVA) as substitutes for traditional PET plastic packaging. Additionally, given the price sensitivity observed under both the RUM and RRM frameworks, pricing strategies need to be continuously explored. It is important to acknowledge that distinguishing between decision-making processes in a marketing context can be challenging, as these processes are often complex, overlapping, and influenced by multiple factors. Recognizing the potential coexistence of both decision-making approaches represents a crucial first step. Future research can further explore methodologies to more effectively differentiate between these two types of decision-makers.

Third, policymakers should consider consumer heterogeneity when designing interventions to reduce plastic packaging waste. Piracci et al. (2023) suggested that policy tools aimed at stimulating individuals' ecological perspectives could prompt individuals to make decisions through the RUM framework. Our findings expand their work by showing that consumers' sustainability considerations can direct their choices through both the RUM and the RRM frameworks. It is therefore essential to account for different cognitive styles and preferences from a broader perspective. Public campaign strategies should also target specific consumer groups, such as fostering trust in food producers or raising awareness about conservation issues, which could be effective in promoting the purchase of sustainable packaging.

Several limitations in our study point to potential directions for future research. First, the environmental advantages of PLA packaging remain debated. Our study focuses on consumer preferences for sustainable packaging but does not examine in depth the degradation of PLA under typical disposal conditions or the technical challenges of its integration into recycling systems. While some PLA packaging can enter the PET recycling system for disposal or degradation, other types often require specific industrial composting conditions, such as high temperature, humidity, and microbial activity, to degrade effectively. This raises concerns about the feasibility of recycling and the potential increased economic costs associated with the process[3] (UN Environment Programme, 2015; van den Oever et al., 2017). Given these limitations, consumer support for PLA packaging alone may not translate to a significant reduction in plastic pollution. To maximize environmental benefits, greater investment in composting infrastructure, clearer consumer guidance on proper disposal, and supportive policies are essential.

Second, while this study focuses on consumer choices related to sustainable packaging, it does not examine the real-world outcomes of these choices. In practice, producers must weigh competitive pressures and cost implications when adopting PLA packaging; governments must evaluate its long-term sustainability, and consumers may not maintain their willingness to pay a premium. Furthermore, as PLA packaging has yet to achieve widespread societal adoption, its actual environmental effectiveness warrants further assessment.

Third, within the RUM and RRM frameworks, our analysis captures heterogeneity arising from factors such as purchase frequency, consumer trust, and conservation awareness; however, other cognitive and behavioral drivers remain unexplored. For example, Biondi et al. (2019) highlight the role of regret sensitivity in shaping consumer choices, while Herrmann et al. (2022) emphasize that perceptions of packaging materials and environmental risk influence purchasing decisions. Future research could further investigate heterogeneity in sustainable packaging preferences by incorporating psychological and perceptual factors such as regret sensitivity, material perception, and environmental risk awareness.

Fourth, this study introduces alternative specifications of alternative specific constants (ASCs) in the discrete choice models to control for unobserved preference imbalances arising from the experimental design and the composition of the sample. It should be emphasized, however, that ASCs primarily capture context specific average effects rather than revealing the underlying mechanisms of individual choice behavior. Future research could combine ASC specifications with more flexible approaches, such as latent class or error components models, to better identify individual-level preference differences. In addition, future work could examine the robustness of ASC specifications for parameter estimation and predictive performance under alternative experimental designs or using real market data. Further discussion could also explore the links between ASCs and behavioral mechanisms such as cognitive complexity, omission bias, or loss aversion (Kahneman et al., 1991; Beshears et al., 2008; Oehlmann et al., 2017).

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Tables

Table 1 Variable Descriptive Statistics

Variables	Mean	Std.Dev.	Description
		Dependent Variable	
Purchase intention	0.250	0.433	=1 if the participant indicates an intention to purchase the option, otherwise = 0.
		Independent Variable	
PLA	0.133	0.340	=1 if the milk packaging is made of PLA; =0 for PET.
TP	0.217	0.412	=1 if the milk packaging is made of TP; =0 for PET.
PVA	0.185	0.388	=1 if the milk packaging is made of PVA; =0 for PET.
Price	49.966	36.049	A continuous variable representing price of the milk.
Date	11.724	10.984	A continuous variable representing the number of days remaining on the date label on the day of purchasing.
Shelflife	0.448	0.497	=1 if the milk has a shelf life of 120 days; and =0 if 30 days.
Optout	0.250	0.433	Alternative specific constant indicating the "no purchase" option in each choice set.
Frequency	4.784	6.268	A continuous variable representing frequency of respondent household milk purchase in the previous month.
Trust	2.542	1.287	A five-point scale representing respondent's trust in the manufacturer producing the food, with 1 indicating "very trustworthy" and 5 indicating "not trustworthy at all."
Awareness	0.548	0.498	=1 if a respondent believes food waste disposal strategies (compost) can reduce food waste behavior, otherwise = 0.
		Demographic Information	
Age	33.338	8.409	A continuous variable representing respondents' age
Female	0.554	0.497	=1 for a female. Otherwise=0.
Income	199.567	12.556	A continuous variable representing the total after-tax income of respondents' household in the previous year, per 1000.
Married	0.766	0.423	=1 for being married. Otherwise=0.
Education	5.662	0.862	A cardinal variable measured with seven levels: 1 for incomplete primary school, 2 for primary school graduate, 3 for middle high school graduate, 4 for high school (technical school/vocational high school) graduate, 5 for 2-year college graduate, 6 for 4-year university graduate, and 7 for graduates with a Master degree or higher.
Hsize	3.399	1.553	A continuous variable representing

			respondents' household size.
Child	0.789	0.571	=1 if a respondent's household has at least one child, otherwise = 0. Children are those under 18.
Elder	0.332	0.693	=1 if a respondent's household has at least one elderly, otherwise = 0. Elders are those over 60.

Note: Our study sample consisted of 612 participants, each of whom was randomly assigned to respond to five choice sets after entering the discrete choice experiment.

Table 2 RUM-CL, RRM-CL, and μRRM-CL Model Estimation Results

	RUM-CL	RRM-CL	μRRM-CL
PLA	0.263***	0.140***	0.137***
	(0.079)	(0.040)	(0.040)
TP	0.092	0.051*	0.049
	(0.061)	(0.031)	(0.031)
PVA	0.084	0.043	0.043
	(0.064)	(0.033)	(0.033)
Price	-0.021***	-0.010***	-0.010***
	(0.001)	(0.000)	(0.001)
Date	0.060***	0.032***	0.031***
	(0.003)	(0.002)	(0.002)
Shelflife	-0.408***	-0.205***	-0.204***
	(0.048)	(0.023)	(0.024)
Optout	-1.388***	-0.525***	-0.574***
	(0.106)	(0.045)	(0.084)
μ			-1.724**
			(0.838)
Log likelihood	-3345.124	-3344.493	-3344.264
AIC	6704.248	6702.987	6704.529
Observations	12240	12240	12240

Note: Standard errors in parentheses; *, **, and ***indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Table 3 RUM-ML and RRM-ML Model Estimation Results

	RUM-ML	RRM-ML
	Fixed parameters	
PLA	0.343***	0.176***
	(0.086)	(0.043)
TP	0.124*	0.069**
	(0.065)	(0.033)
PVA	0.085	0.041
	(0.063)	(0.035)
Price	-0.023***	-0.011***
	(0.002)	(0.001)
Date	0.064***	0.035***
	(0.004)	(0.002)
	Random parameters	
Shelflife	-0.448***	-0.221***
	(0.064)	(0.030)
Optout	-2.684***	-1.089***
	(0.217)	(0.097)
	Standard deviations of random parameters	
Sd-Shelflife	0.788***	0.401***
	(0.092)	(0.043)
Sd-Optout	2.254***	1.058***
	(0.213)	(0.092)
Log likelihood	-3186.359	-3186.117
AIC	6390.718	6390.233
Observations	12240	12240

Note: Standard errors in parentheses; *, **, and ***indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Table 4 Hybrid RUM-RRM and RUM-μRRM Models Estimation Results

	RUM-RRM Model		RUM-μRRM Model	
	RUM-CL	RRM-CL	RUM-CL	μRRM-CL
PLA	0.457***	0.185*	0.423**	0.233**
	(0.127)	(0.089)	(0.136)	(0.090)
TP	0.353**	0.179*	0.338**	0.164*
	(0.117)	(0.084)	(0.129)	(0.082)
PVA	0.383***	0.147**	0.390***	0.122*
	(0.100)	(0.057)	(0.106)	(0.054)
Price	0.007**	-0.022***	0.008**	-0.021***
	(0.002)	(0.002)	(0.003)	(0.002)
Date	0.048	0.067***	0.047	0.063***
	(0.009)	(0.003)	(0.009)	(0.003)
Shelflife	-0.089	-0.253	-0.040	-0.327
	(0.157)	(0.064)	(0.168)	(0.055)
Optout	0.040***	0.037***	-0.023***	-0.069
	(36.416)	(16.730)	(8.954)	(312.893)
μ				0.481
				(0.069)
Membership Probability	0.382	0.618	0.356	0.644
Age	-0.009	0.009	-0.010	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Female	-0.194	0.194	-0.219*	0.219*
	(0.106)	(0.106)	(0.107)	(0.107)
Income	0.007	-0.007	0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Married	0.074	-0.074	0.073	-0.073
	(0.172)	(0.172)	(0.177)	(0.177)
Education	0.0143	-0.0143	0.010	-0.010
	(0.042)	(0.042)	(0.043)	(0.043)
Hsize	-0.092	0.092	-0.089	0.089
	(0.068)	(0.068)	(0.069)	(0.069)
Child	0.233	-0.233	0.245	-0.245
	(0.129)	(0.129)	(0.130)	(0.130)
Elder	0.065	-0.065	0.055	-0.055
	(0.096)	(0.096)	(0.100)	(0.100)
Log likelihood	-3175.482		-3166.825	
AIC	6410.965		6395.650	
Observations	12240		12240	

Note: Standard errors in parentheses; *, **, and ***indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Table 5 WTP for Types of Milk Packaging (unit: yuan/2880ml carton)

	Package Types	WTP Estimates	95% Confidence Interval
	PLA	13.996***	[6.31, 21.88]
μRRM-CL	TP	4.969	[-1.10, 11.20]
	PVA	4.342	[-1.95, 10.95]
	PLA	14.722***	[7.78, 21.67]
RUM-ML	TP	5.318	[-0.23, 10.86]
	PVA	3.654	[-1.69, 8.99]
	PLA	16.769***	[8.70, 24.35]
RRM-ML	TP	6.478**	[0.22, 12.71]
	PVA	3.855	[-2.61, 10.62]

Note: Following Chorus et al. (2012), the RRM-based measures of WTP are conditional on the chosen alternative. Accordingly, they are first calculated for each choice set and then averaged across all choice sets. The confidence intervals are derived from 5,000 simulations.

Table 6 Estimation of the RUM-CL, RRM-CL, and μRRM-CL Models with Interactions

	RUM-CL	RRM-CL	μRRM-CL	RUM-CL	RRM-CL	μRRM-CL	RUM-CL	RRM-CL	μRRM-CL
PLA*Frequency	0.036***	0.020***	0.019***						
	(0.009)	(0.005)	(0.005)						
TP*Frequency	0.012*	0.007*	0.007*						
	(0.007)	(0.004)	(0.004)						
PVA*Frequency	0.012	0.006	0.006						
	(0.008)	(0.004)	(0.004)						
PLA*Trust				0.061**	0.033**	0.032**			
				(0.026)	(0.013)	(0.013)			
TP*Trust				0.029	0.016	0.016			
				(0.020)	(0.010)	(0.010)			
PVA*Trust				0.023	0.012	0.012			
				(0.022)	(0.011)	(0.011)			
PLA*Awareness							0.532***	0.279***	0.274***
							(0.097)	(0.052)	(0.051)
TP*Awareness							0.139*	0.074*	0.072*
							(0.078)	(0.040)	(0.040)
PVA*Awareness							0.172**	0.087**	0.086**
							(0.085)	(0.043)	(0.043)
Price	-0.021***	-0.010***	-0.010***	-0.021***	-0.010***	-0.010***	-0.022***	-0.010***	-0.010***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Date	0.060***	0.032***	0.032***	0.060***	0.032***	0.032***	0.060***	0.032***	0.031***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Shelflife	-0.398***	-0.201***	-0.200***	-0.391***	-0.197***	-0.196***	-0.415***	-0.208***	-0.207***
	(0.047)	(0.023)	(0.023)	(0.047)	(0.023)	(0.023)	(0.047)	(0.023)	(0.023)
Optout	-1.378***	-0.525***	-0.572***	-1.351***	-0.514***	-0.567***	-1.404***	-0.530***	-0.587***
	(0.102)	(0.044)	(0.081)	(0.104)	(0.044)	(0.082)	(0.102)	(0.044)	(0.085)
μ			-1.729**			-1.645*			-1.636*
			(0.833)			(0.895)			(0.901)
Log likelihood	-3341.532	-3340.889	-3340.662	-3347.963	-3347.504	-3347.2057	-3334.493	-3334.030	-3333.722
AIC	6697.064	6695.778	6697.323	6709.927	6709.009	6710.411	6682.986	6682.060	6683.445
Observations	12240	12240	12240	12240	12240	12240	12240	12240	12240

Note: Standard errors in parentheses; *, **, and ***indicate significant at the 10%, 5%, and 1% significance levels, respectively.

Table 7 Estimation of the RUM-ML and RRM-ML Models with Interactions

	RUM-ML	RRM-ML	RUM-ML	RRM-ML	RUM-ML	RRM-ML
Fixed parameters						
PLA*Frequency	0.035***	0.019***				
	(0.011)	(0.005)				
TP*Frequency	0.009	0.005				
	(0.008)	(0.004)				
PVA*Frequency	0.006	0.003				
	(0.008)	(0.004)				
PLA*Trust			0.086***	0.045***		
			(0.029)	(0.015)		
TP*Trust			0.042*	0.023**		
			(0.022)	(0.011)		
PVA*Trust			0.026	0.012		
			(0.022)	(0.012)		
PLA*Awareness					0.606***	0.316***
					(0.116)	(0.054)
TP*Awareness					0.146*	0.080*
					(0.087)	(0.044)
PVA*Awareness					0.158*	0.079*
					(0.084)	(0.047)
Price	-0.022***	-0.010***	-0.022***	-0.010***	-0.023***	-0.011***
	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)
Date	0.065***	0.035***	0.065***	0.035***	0.065***	0.035***
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
Random parameters						
Shelflife	-0.426***	-0.211***	-0.426***	-0.211***	-0.451***	-0.223***
	(0.063)	(0.029)	(0.063)	(0.030)	(0.063)	(0.030)
Optout	-2.649***	-1.081***	-2.634***	-1.077***	-2.681***	-1.086***
	(0.216)	(0.095)	(0.215)	(0.097)	(0.216)	(0.096)
Standard deviations of random parameters						
Sd-shelflife	0.770***	0.391***	0.777***	0.395***	0.794***	0.404***
	(0.091)	(0.043)	(0.091)	(0.043)	(0.092)	(0.043)
Sd-optout	2.228***	1.046***	2.250***	1.063***	2.226***	1.044***

	(0.211)	(0.091)	(0.212)	(0.093)	(0.214)	(0.091)
Log likelihood	-3186.977	-3186.683	-3190.029	-3189.802	-3176.627	-3176.632
AIC	6391.953	6391.370	6398.059	6397.604	6371.255	6371.264
Observations	12240	12240	12240	12240	12240	12240

Note: Standard errors in parentheses; *, **, and ***indicate significant at the 10%, 5%, and 1% significance levels, respectively.

[1] The national population characteristics are from the 2020 Population Census of China. https://www.stats.gov.cn/sj/pcsj/rkpc/d7c/202303/P020230301403217959330.pdf.

[2] We recognize that awareness of food waste disposal strategies does not necessarily equate to concern about the environmental impact of food waste. However, our approach assumes that such awareness reflects a certain level of attentiveness to environmental or conservation issues.

[3] In many countries, including China, consumers pay for both the beverage and its package, but disposal practices differ. While Western countries rely on formal deposit–refund systems, China's extensive informal recycling network enables discarded packages to be resold and treated properly, increasing the likelihood of PLA biodegradation and reducing unmanaged waste.