

Narrowing consumers' supply-demand knowledge gap: Impact of health or sustainability information interventions in driving food loss reduction

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1 **Narrowing consumers' supply-demand knowledge gap: Impact of health or**
2 **sustainability information interventions in driving food loss reduction**

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9 ABSTRACT

10 Imperfect information about supply-side food-loss reduction benefits may reduce
11 consumers' demand for food-saving products, exacerbating food insecurity issues.
12 Health and sustainability information interventions are increasingly integrated into
13 effective policy designs driving sustainable food transformation, but the ways in which
14 consumer preferences for supply-side food-loss reduction are shaped, and to what
15 extent, requires further investigation. Given the lack of comparative studies, this study
16 systematically compares the effects of health-oriented versus sustainability-oriented
17 information interventions on the preferences for food-loss reduction labeled rice. To
18 identify the effects, we employ randomized information interventions and discrete
19 choice experiments, covering 1,469 rice consumers in China. The results indicate that:
20 (1) Both types of information interventions notably enhance consumers' preferences for
21 low-loss labeled rice, but through varying pathways. Health information increases
22 consumers' valuation of health attributes, whereas sustainability information primarily
23 strengthens preferences for the food-loss reduction technology itself. (2) Consumer
24 characteristics significantly moderate these effects. Health information is particularly
25 effective for high-income and older consumers, while sustainability information exerts
26 stronger incentives for households with more members. (3) The interventions exhibit
27 heterogeneous effects across a range of psychological dimensions. Health information
28 demonstrates broad applicability, enhancing preferences across groups with varying
29 attitudes toward food conservation and perceived efficacy, whereas sustainability
30 information mainly benefits consumers with strong pro-environmental attitudes. This
31 study underscores the differential pathways through which self-oriented versus
32 altruistic information shapes consumer preferences. These findings provide empirical
33 guidance for designing targeted information interventions to foster food loss reduction
34 and support efficiency improvements across the food supply chain from the demand
35 side.

36 **Keywords:** health information intervention; sustainability information intervention;
37 consumer preference; food-loss reduction label; discrete choice experiment

1 Introduction

Growing food loss and waste, including supply-side food losses at production and post-harvest stages and demand-side food waste at retailer and consumer levels, is a critical issue that persists globally, worsening food security (Madadi et al., 2025). Approximately one-third of all food produced---amounting to about 1.3 billion tons---is lost or wasted along the food supply chain each year (FAO, 2019), causing detrimental consequences such as environmental degradation (Spang et al., 2019), inefficient resource use (Aslam et al., 2024; Agya, 2025), and economic losses (Mak et al., 2020). During the last years, a substantial amount of research have focused primarily on developing interventions for mitigating demand-side food waste (Chai et al., 2024; Lohmann et al., 2026; Zhu et al., 2023; Roodhuyzen et al., 2017). Notably, despite the untapped reduction potential that exists in on-farm food loss based on available quantified estimates (Xue et al., 2021; Zhu et al., 2023), little attention has given to supply-embodied food loss in policy circles, academia, and the private sector. Such inefficiencies would imply that there exist considerable potential benefits to supply-side food reductions for individuals, organizations, and governments (Aschemann-Witzel et al., 2023; Kashyap et al., 2024).

Reducing supply-side food loss using the market-incentive pathway is identified as a critical lever in achieving food security (Lohmann et al., 2026) and fostering progress toward the United Nations Sustainable Development Goals (SDGs) (Anand & Barua, 2022; Hoehn et al., 2023). Increasing consumer demand for supply-side food loss reduction could serve as a critical driver for advancing food security. However, asymmetric information is ubiquitous across the developing world (Hasanain et al., 2023; Wild et al., 2012) and often leads to supply-demand knowledge gap that supply-side food loss information available does not match current demand-side consumers' needs. As consumer food needs evolve (Inguglia et al., 2023), interest in food origin, production methods, and characteristics grows (Joltreau, 2022; Karlsson et al., 2023), driving increasing demand for food information (Aprile & Punzo, 2022). However, the health, safety, and environmental attributes embedded in loss-reduction technologies and products are often credence attributes, i.e., unverifiable by consumers at the point

of purchase (Darby & Karni, 1973; Aprile & Punzo, 2022). This information asymmetry creates a gap between producers and consumers. Existing research has demonstrated that food labels are key to addressing the information asymmetry between producers and consumers in food markets (Wongprawmas & Canavari, 2017) and can help consumers make rational choices (Robertson et al., 2023). However, food labels alone are insufficient to effectively change consumer behavior; greater attention needs to be paid to the role of information in shaping consumer behavioral change (Ran, 2022). Therefore, how to help consumers identify and trust the credence attributes carried by food loss reduction labels through effective information interventions becomes the key to promoting whole-chain loss reduction efficiency from the demand side.

Currently, several commonly used behavioral change interventions are employed to alter consumer behavior, including education and information initiatives, restrictions or increases in product availability, and economic incentives (Lindahl & Jonell, 2020; Grilli & Curtis, 2021; Rööß et al., 2021; Ran et al., 2022). Among these, information measures are widely applied because they are relatively easy to implement (Lindahl & Jonell, 2020; Grilli & Curtis, 2021). A large body of research shows that information interventions affect consumer preferences (Bateman et al., 2009; Bougherara & Combris, 2009) and are effective tools for changing consumer behavior (Lin & Nayga, 2022; Li et al., 2025). From the perspective of consumer motivation, two main types of motives—self-interest and altruism—influence consumer decision-making (Honkanen & Olsen, 2006). Consumers increasingly value information related to health and sustainability (Aschemann-Witzel, 2015; Verain et al., 2016; Aschemann-Witzel et al., 2019). Health information activates consumers' self-interested motives (Aschemann-Witzel, 2015; Ammann et al., 2025); such interventions not only increase knowledge and improve consumers' health literacy but also lead to behavioral changes, shifting their preferences toward nutritionally balanced foods (Leveré et al., 2016). Sustainability information, by contrast, activates altruistic motives (Aschemann-Witzel, 2015; Ammann et al., 2025); such information enhances consumers' sense of social responsibility and increases their preference for purchasing goods with desirable characteristics. These perspectives generally align with extant research to reveal the

effectiveness of information interventions as a means to motivate consumers' food-loss reduction intention and address food security concerns (Lohmann et al., 2026; Jia & McNamara, 2024).

This paper adds to the body of existing literature in several ways. First, from the perspective of self-interested versus altruistic consumption motives, this work contributes to the food consumption literature by exploiting two sources of information interventions related to health and sustainability. Although the empirical and theoretical literature demonstrate the significance of sustainability and health information intervention in shaping consumers' behaviors (Aschemann-Witzel, 2015; Verain et al., 2016; Aschemann-Witzel et al., 2019), the potential of mitigating food loss is underexplored. Most studies examine the effect of a single information intervention in isolation (Lin & Nayga, 2022; Katare et al., 2025). This work attempts to compare the differential effects of health-oriented versus sustainability-oriented information interventions on consumer decisions. This provides important theoretical and empirical support for the precise design of information intervention content and the achievement of policy objectives. Second, this paper contributes to a better understanding of the heterogeneous effects of information interventions. Previous studies have largely focused on the average treatment effects of information interventions, overlooking their heterogeneous nature. In fact, the effects of information interventions are not homogeneous; rather, they are shaped by preference heterogeneity arising from the combined influence of consumers' personal characteristics and psychological cognitive variables (Vittuari et al., 2023). Extending the traditional focus on average treatment effects, this study incorporates both personal characteristics and psychological cognitive variables to explore the sources and underlying mechanisms of heterogeneity in information intervention effects. This offers a scientific basis for policymakers to implement differentiated intervention strategies tailored to individual characteristics. Third, this work informs a stream of research investigating the effect of information interventions on consumers' response to food loss reduction. On the emerging issue of food loss reduction, consumers' awareness and preferences regarding food loss reduction labels themselves have not been sufficiently validated. There is still a lack of

systematic empirical research on whether and how information interventions of different content affect consumers' willingness to pay for loss-reduction-related attributes (Lohmann et al., 2026; Vittuari et al., 2023). This study complements the literature by studying the effects of health and sustainability information using a discrete choice experiment to simulate real market condition.

Based on this, the present study conducted a randomized experiment using information interventions with 1,469 rice consumers and employed a discrete choice experiment (DCE) to systematically compare differences in consumer preferences and willingness to pay among a health information group, a sustainability information group, and a no-information group. The study explores the effects of different types of information interventions on consumer preferences for rice with food loss reduction labels and further reveals the underlying mechanisms of these effects.

2 Theoretical framework and hypotheses

2.1 Micro-Utility Theory and Information Asymmetry

Lancaster's (1966) microeconomic theory of utility suggests that the utility consumers derive from a product does not originate directly from the product itself, but rather from its various attributes and characteristics. Essentially, consumers' choice of a product is an expression of their preference for a specific combination of product attributes. Food is regarded as a bundle comprising multiple quality attributes. When deciding whether to purchase a product, consumers assess and compare food quality attributes, either objectively or subjectively, based on available and credible information (Wu et al., 2021). Information economics theory classifies food quality attributes into search attributes, experience attributes, and credence attributes (Schroback et al., 2023). Among these, credence attributes refer to food quality characteristics that consumers cannot independently judge or evaluate at the point of sale through search (e.g., price, appearance) or experience (e.g., taste, texture) (Darby & Karni, 1973). However, in the process of information transmission, the observability of information is an important prerequisite for ensuring its effectiveness (Allon &

Bassamboo, 2011). When consumers are unable to assess the presence of credence attributes unless additional information (such as labels) is provided, this implies that producers in market transactions possess more information than consumers—a situation referred to as information asymmetry within food markets (Caswell & Mojduszka, 1996).

Information asymmetry theory posits that when one party in a transaction has information that the other party cannot access, market failure may occur (Akerlof, 1978). Only when such information is appropriately disclosed through specific information instruments can consumers take it into account in their decision-making processes (Aprile & Punzo, 2022). Research indicates that in purchasing situations characterized by products with credence attributes, the specific information signals provided by labels can overcome information asymmetry (Aprile et al., 2012). Food labels, as a standardized information transmission tool, are key to addressing information asymmetry between producers and consumers in food markets (Wongprawmas & Canavari, 2017) and can help consumers make rational choices (Robertson et al., 2023). Labels present the implicit attributes of products to consumers in a standardized manner, not only reducing consumers' information search costs but also providing the technical prerequisite for consumers to incorporate product attributes into their utility evaluation. The food loss reduction label, as an information transmission tool, visualizes the technologies and effects related to food loss reduction, thereby reducing consumers' information search costs. It can both foster social recognition of loss-reducing consumption and internalize external costs through the price mechanism, generating market-driven incentives for loss reduction.

2.2 Mechanisms of Information Interventions on Consumer Preferences

Relying solely on food labels is difficult to effectively change consumer behavior; greater attention needs to be paid to the role of information in shaping consumer behavioral change (Ran, 2022). In information economics, information is a credible clue transmitted from producers to consumers regarding unobservable product quality (Wells et al., 2011) and is an important tool for inducing consumer change (Bateman et al., 2009). Signaling theory suggests that producers with a higher level of product

information proactively provide information to consumers with a lower level of product information in order to reduce information asymmetry between the transacting parties, thereby facilitating transactions (Spence, 1978). Information interventions play an important role in shaping consumer preferences (Bateman et al., 2009; Bougherara & Combris, 2009) and are effective tools for changing consumer behavior (Lin & Nayga, 2022). In consumers' purchase decision-making processes, information interventions not only help increase consumers' knowledge stock, improve their attitudes toward food, and enhance their risk perception abilities, but also promote the formation of good habits and foster a positive atmosphere and cultural environment that values food safety (Young & Waddell, 2016). When a product is endowed with a noble moral meaning, consumers tend to assign additional value to it, thereby generating preferences that go beyond price rationality (Ahn et al., 2016; Bougherara & Combris, 2009; Ding et al., 2023).

Information is key to influencing how agents process information and make behavioral decisions, but different types of information have distinct mechanisms of influence on individual behavior. Although information interventions present multiple classifications due to the different information dimensions on which scholars focus, from the perspective of consumer motivation, self-interest and altruism are the main behavioral motives influencing consumer decision-making (Honkanen & Olsen, 2006; He et al., 2025). Consumers increasingly value information related to health and sustainability (Aschemann-Witzel, 2015; Verain et al., 2016; Aschemann-Witzel et al., 2019). Therefore, this study designs two types of information interventions to explore the mechanisms through which different information interventions affect consumer preferences. On the one hand, health is an important factor in consumers' food purchases (Alsubhi & Blake, 2023; Sonnenberg et al., 2013). Consumers are more concerned than ever about their personal health and well-being, are willing to pay a premium for products, and are shifting from traditional brands to those that provide more informative product labels (Kerry, 2023). Health information interventions, by elaborating on the benefits of food loss reduction technologies in preserving nutrition and avoiding the safety risks of moldy food, aim to correct individual cognitive biases

and ultimately achieve the transformation from intrinsic motivation to external action, influencing consumer decisions from the perspective of self-interested motives (Aschemann-Witzel, 2015; Ammann et al., 2025). On the other hand, consumers are increasingly concerned about environmental and social sustainability, paying attention to how food is produced and where it originates (Karlsson et al., 2023), and are willing to pay a reasonable premium for socially responsible products (Laroche, 2001; Nikolaou & Kazantzidis, 2016) and sustainably produced food (Rossi et al., 2024). Sustainability information interventions focus on presenting the contribution of food loss reduction technologies to ensuring the stability of the food supply chain and promoting the sustainable use of resources. Their purpose is to transform individual cognition, striving to enhance the sense of social responsibility and moral identity, and influence consumer decisions from the perspective of altruistic motives (Aschemann-Witzel, 2015; Ammann et al., 2025). Based on this, this study proposes the following research hypotheses:

H1: Compared with the no-information intervention, both health information intervention and sustainability information intervention increase consumer preferences.

H2: The pathways of influence differ between the two types of information interventions; specifically, health information primarily works by enhancing consumers' preferences for health-related attributes, whereas sustainability information primarily works by enhancing consumers' preferences for loss reduction technology attributes.

2.3 Consumer Heterogeneity Analysis

Consumer preferences are characterized by heterogeneity (Foellmi & Zweimüller, 2006), and the effects of information interventions are not homogeneous but are shaped by the combined influence of consumers' individual characteristics and psychological cognition (Vittuari et al., 2023). Consumers' individual characteristics are considered to have an indirect impact on their food waste behavior (van Geffen et al., 2020), among which age, gender, education level, household size, and income are the most common and relevant factors (Van Geffen et al., 2016). Furthermore, consumers can be segmented into different groups based on their underlying psychological drivers of food

loss and waste, and such segmentation can serve as a methodological foundation for designing tailored food loss reduction interventions for specific consumer groups (Vittuari et al., 2023). Information, by enhancing cognition and transmitting knowledge, forms or changes individuals' existing cognitions and attitudes (Van Kleef et al., 2005; Krystallis et al., 2008). The theory of planned behavior indicates that an individual's attitude toward a specific behavior is a key antecedent variable for predicting their behavioral intention (Ajzen, 1991, 2002). When the value proposition conveyed by an information intervention is highly consistent with consumers' intrinsic values, the intervention reinforces consumers' sense of identification with and perceived credibility of the information, thereby amplifying the positive impact of the information on their preferences. Conversely, consumers with low attitudes lack the corresponding intrinsic value basis and may respond weakly or even indifferently to similar information (Vittuari et al., 2023). Protection motivation theory offers another perspective for understanding how information persuades individuals to change their behavior. This theory emphasizes that an individual's motivation to adopt coping measures depends on their assessment of the severity of the threat and their evaluation of the effectiveness of the coping measures (Rogers, 1975). Consumers with high perceived efficacy have strong confidence in the effectiveness of loss reduction technologies and in their own contributions; their behavior may be more driven by intrinsic beliefs. In contrast, consumers with low perceived efficacy may experience cognitive barriers due to doubts about the technology or their own role. Based on this, this study proposes the following research hypotheses:

H3: The effects of information interventions on consumer preferences are heterogeneous with respect to individual characteristics.

H4: The effects of information interventions on consumer preferences are heterogeneous with respect to attitudes toward food conservation.

H5: The effects of information interventions on consumer preferences are heterogeneous with respect to perceived response efficacy of loss reduction.

3 Methods

3.1 Data Source

With the rapid development and widespread adoption of mobile internet technology, the sample bias associated with online survey methods is rapidly decreasing (Windle & Rolfe, 2011). Online surveys can save survey time, reduce data entry errors, and mitigate the sample selection bias that may arise from high refusal rates in traditional survey methods. Consequently, they have been widely used in consumer surveys in recent years (Zhou et al., 2017). Therefore, this study conducted a randomly sampled online questionnaire survey through Sojump platform (<https://www.wjx.cn>, similar to “Synata”). This platform has more than 6.2 million registered users, of which over 3 million are active, covering 31 provincial-level administrative regions in China (excluding Hong Kong, Macao, and Taiwan).

Before the formal survey, this study used pilot survey data from 106 rice consumers as prior values for the Bayesian design to optimize the D-efficiency of the random prior, ultimately obtaining the formal choice experiment cards. After adjusting and refining the experimental protocol and the questionnaire, the research team formally administered the survey and collected questionnaires in May 2025. Respondents were required to be at least 18 years old and *had* purchased rice within the past six months. In addition, several attention-check questions were embedded in the questionnaire; participants who failed to answer these attention-check questions were automatically excluded. A total of 1,583 questionnaires were distributed. After excluding 114 invalid questionnaires that had completion times shorter than 100 seconds or exhibited completely consistent responses on scale items, 1,469 valid questionnaires were obtained, yielding an effective response rate of 92.80%.

3.2 Information Intervention Experiment Design

Different types of information have different mechanisms of influence on individual behavior. Drawing on existing research (Aschemann-Witzel et al., 2019), this study designed three conditions: a health information intervention, a sustainability information intervention, and a no-information control group. The information intervention was implemented before consumers participated in the choice experiment. To avoid endogeneity bias arising from self-selection, the questionnaire was designed

to ensure that each respondent was randomly assigned to the health information group, the sustainability information group, or the no-information control group with equal probability, as detailed below. (1) Health information group: Respondents in this group were presented with a set of text and images focusing on the positive benefits of food loss reduction technologies for consumer health, including preserving the native nutrition of food, avoiding potential food safety hazards, and reducing the risk of harmful substance intake. (2) Sustainability information group: Respondents in this group were presented with another set of text and images, mainly explaining the important role of food loss reduction technologies in ensuring the stability of the food supply chain and promoting the sustainable use of resources, thereby illustrating their positive significance for sustainable development. (3) Control group: Respondents in this group were not provided with any additional information related to food loss reduction. To ensure that respondents had sufficient time to read the information, they were unable to proceed with the questionnaire for 30 seconds.

3.3 Discrete Choice Experiment Design

Determining product attributes and attribute levels is key to the choice experiment method. Selenium-enriched certification, national geographical indication certification, and price are common attributes of rice (Zhang et al., 2023). On this basis, this study adds attributes related to food loss reduction labels and technologies. The Multiple Traffic Lights (MTL) labels have been demonstrated to be superior in terms of comprehensibility, comparability, and interpretability (Temple & Norman, 2020; Dreist et al., 2025). Therefore, drawing on existing label design systems (Hagmann & Siegrist, 2020), this study sets three levels for the food loss reduction label: low loss rate, high loss rate, and no label. The labels are designed in red and green colors, using visual cues such as color codes to convey the assessment of product loss levels. Technological innovation has gradually become an important means of reducing food loss (Morone et al., 2019; Agya, 2025). The main stages of food loss in China are production, post-harvest handling and storage, and distribution (Xue et al., 2021). Loss reduction technologies such as hermetic storage bags (Mbesa et al., 2025; Agya, 2025), mechanization (Emami et al., 2021; Castelein et al., 2022), and intelligent production

(Trevisan & Formentini, 2023) can effectively reduce physical losses during production, storage, and transportation. Accordingly, this study designs two attributes—food loss reduction technology in the production stage and food loss reduction technology in the storage stage—each with three corresponding levels. The specific attributes and levels are shown in Table 1.

Table 1. Attributes and Levels for the Discrete Choice Experiment

Attribute	Levels
Food Loss Reduction Label	Low-loss, High-loss, No label
Production-stage Loss Reduction Technology	Manual production, Mechanized equipment, Intelligent production technology
Storage-stage Loss Reduction Technology	Traditional stacking, Sealed bag packaging, Cold chain storage
Selenium-enriched Certification	Yes, No
National Geographic Indication Certification	Yes, No
Price (CNY per 500g)	2, 6, 10, 14

According to the product attributes and their specific levels set in Table 1, a full factorial design would generate 432 possible product profiles ($3^3 \times 2^2 \times 4 = 432$), and respondents would complete 93,096 choice tasks ($C_{432}^2 = 93,096$), which is clearly unrealistic. Respondents tend to become fatigued after completing 15–20 choice scenarios, and too many choices set lead to excessive cognitive burden (Allenby & Rossi, 1998). Therefore, this study employed a fractional factorial design developed using Ngene software, generating 48 choice sets based on a D-efficiency exceeding 90%, which were then randomly divided into four blocks. To prevent consumers participating in the survey from being forced to make a choice and to ensure the authenticity of the experiment, an opt-out option (“none of these”) was added to each choice set (Dhar, 1997). In the market, rice label attributes are mostly presented in the form of icons. To give consumers an intuitive understanding of the product and to make the experiment more consistent with real-world choice situations, the label attributes in the choice scenarios are represented by icons. China has established clear icons for selenium-enriched certification and national geographical indication certification. An example of the final designed choice scenario is shown in Figure 1. Before making their choices, respondents were asked to read the instructions regarding each attribute and level of the discrete choice experiment to ensure that they understood the relevant

concepts involved in the choice scenarios. Consequently, they were unable to proceed with the questionnaire for 40 seconds.



Figure 1. Example of a Choice Scenario in the Discrete Choice Experiment

3.4 Econometric Model Specification

Random utility theory (RUT) provides the empirical foundation for discrete choice experiments (McFadden, 1972). $U_{n,i,t}$ denote the utility that consumer n derives from choosing product i in choice scenario t . The utility consists of a deterministic component $\beta X_{n,i,t}$, a random error term $\varepsilon_{n,i,t}$, and an alternative-specific constant (ASC). Consumers make choices by comparing the utility levels of available alternatives within the choice set. Correspondingly, the multinomial logit (MNL) model is employed to estimate the choice probabilities. Specifically, the utility that consumer n obtains from selecting product i in scenario t (where $i=1$ represents Rice 1, $i=2$ represents Rice 2, and $i=3$ represents “none of these”) can be expressed as a function of the random utility components as specified above.

$$U_{n,i,t} = \beta X_{n,i,t} + \varepsilon_{n,i,t} + ASC \quad (1)$$

In the above equation, β represents the vector of utility coefficients, capturing individual preferences; $X_{n,i,t}$ denotes the vector of attributes for rice product i available to consumer n in choice scenario t ; and ASC is the alternative-specific constant. The ASC takes a value of 1 if the consumer selects the “none of these” option, and 0 if the consumer chooses either of the two rice alternatives.

Assuming consumers are rational, they choose the product that yields the highest utility. The probability of selecting a given alternative is therefore determined by the relative utility levels, which forms the basis for the multinomial logit (MNL) model. Under the standard assumption that the random error term $\varepsilon_{n,i,t}$ is independently and identically distributed following an extreme value distribution, the probability that consumer n selects rice product i from j available alternatives in scenario t can be expressed as:

$$P_{n,i,t} = \frac{\text{Exp}(\beta X_{n,i,t})}{\sum_j \text{Exp}(\beta X_{n,i,t})} \quad (2)$$

Since product attributes influence consumers' utility levels, these preferences can be partially translated into willingness-to-pay (WTP) measures for the respective attributes (Ortega et al., 2011, 2015). Assuming that total utility is a linear additive function of the utilities derived from individual food attributes and price, the WTP for a given attribute can be calculated as follows:

$$WTP_j = -\frac{\beta_j}{\beta_p} \quad (3)$$

In the above equation, WTP_j represents the willingness-to-pay for the j -th attribute level; β_j denotes the estimated coefficient for that attribute level; and β_p is the estimated coefficient for price.

In the baseline model, the effects of attributes are assumed to be independent. However, in reality, individuals' sensitivity to product attributes may vary according to their personal characteristics. To capture this heterogeneity, demographic interaction terms are incorporated into the baseline regression model to examine the underlying mechanisms driving consumer choice preferences. The utility function can then be expressed as:

$$U_{n,i,t} = \beta X_{n,i,t} + \gamma(X_{n,i,t} \times Z_n) + \varepsilon_{n,i,t} + ASC \quad (4)$$

In the above equation, Z_n denotes a vector of demographic characteristics for consumer n , and γ represents the coefficients of the interaction terms between product attributes and consumer demographics. This specification allows the model to account for heterogeneity in attribute sensitivities and provides a more nuanced understanding of the determinants of consumer preferences.

Finally, a Random Parameter Logit (RPL) model was employed for robustness checks. The RPL model is highly flexible and can accommodate any random utility specification. By allowing parameters to vary within the sample according to a specified distribution, it relaxes the restrictive assumptions of the traditional Logit model (McFadden & Train, 2000). Moreover, the model is particularly effective for handling situations in which a single respondent makes multiple choices (Brownstone & Train, 1998). It is a widely used method for assessing preference heterogeneity, providing a robust framework for analyzing decision-making behavior when sample-level heterogeneity exists. The probability of a consumer's choice under the RPL model can be expressed as follows:

$$P_{ni} = \int \frac{\exp(x'_{ni}\beta)}{\sum_{j=1}^J \exp(x'_{ni}\beta)} f(\beta|\theta) d\beta \quad (5)$$

In the above equation, β denotes a vector of consumer-specific parameters, and $f(\beta|\theta)$ represents the density function of β .

4 Results and Discussion

4.1 Sample Characteristics and Descriptive Statistics

This study selected gender, age, education level, household size, and income as demographic characteristics (Van Geffen et al., 2016; Miller et al., 2022). Table 2 presents the variable assignments and descriptive statistics. Among the consumers surveyed, the proportions of males and females were roughly similar. The average age of consumers was 38.43 years, with young (22–34 years), middle-aged (35–59 years), and elderly (60 years and above) consumers accounting for 44.18%, 45.54%, and 10.28% of the sample, respectively. Respondents with a college degree or above accounted for 58.61% of the sample, indicating a relatively high average education level. The average household size was 4.15 persons per household, slightly higher than the national census average of 2.62 persons per household. The average monthly household income per capita was 4,071.60 RMB, slightly higher than the national per capita disposable monthly income of 3,614.75 RMB in 2025. Overall, the sample in this study is broadly representative of the basic demographic profile of the Chinese population, while

tending to skew toward younger, highly educated, and higher-income groups. This is consistent with trends observed in internet-based food surveys in China (Yang et al., 2020; Shi et al., 2025).

Table 2. Descriptive Statistics of Respondents' Demographic and Psychological Characteristics

Variable	Definition and Coding	Full Sample	Health Information Group	Sustainability Information Group	No-Information Control Group
Gender	Male = 1; Female = 2	1.4309 (0.4954)	1.4394 (0.4968)	1.4473 (0.4978)	1.4055 (0.4915)
Age	Respondent's age in years	38.4261 (12.8530)	38.4015 (13.1145)	39.3527 (12.8291)	37.5483 (12.5438)
Education	No schooling = 1; Primary education (preschool/elementary) = 2; Secondary education (junior/senior high) = 3; Higher education (college/undergraduate/adult education) = 4; Graduate education (Master/PhD) = 5	3.4561 (0.8305)	3.4545 (0.8367)	3.4280 (0.8708)	3.4853 (0.7826)
Household Size	Total number of household members	4.1484 (1.3236)	4.1894 (1.2678)	4.0989 (1.3224)	4.1513 (1.3850)
Income	Average monthly income per household member (CNY/month)	3963.44 (3144.43)	3979.04 (3114.69)	3954.32 (3267.43)	3955.04 (3060.19)
Food Security Response Efficacy	"Use of loss reduction technologies can significantly reduce food loss; government-promoted loss reduction measures can effectively alleviate food security issues; even using loss reduction technology, it is difficult to significantly improve food security." (Strongly disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; Strongly agree = 5)	3.5368 (0.9535)	3.5196 (0.9446)	3.5473 (0.9784)	3.5457 (0.9402)
Food Security Self-Efficacy	"I am willing to invest time and effort to learn about food security; I am willing to promote the importance of food loss reduction to those around me; individual actions have limited effect on loss reduction." (Strongly disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; Strongly agree = 5)	3.4217 (0.9760)	3.4081 (0.9542)	3.4152 (0.9751)	3.4430 (1.0022)
Food Security Response Barriers	"Insufficient societal attention to food loss reduces my willingness to participate; purchasing products using loss reduction technology increases household expenses; existing policies have fully addressed barriers to technology adoption." (Strongly disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; Strongly agree = 5)	3.6067 (0.7882)	3.5842 (0.7677)	3.5734 (0.7981)	3.6641 (0.8016)
Food Waste Attitude	"Producing food is an honorable occupation; conserving food is honorable; wasting food is shameful." (Strongly disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; Strongly agree = 5)	4.0495 (0.6938)	4.0470 (0.6693)	4.0655 (0.6991)	4.0367 (0.7160)
Food Waste Subjective Norm	"In the past year, have you participated in food conservation activities? Do you discuss food loss with family, colleagues, friends, or neighbors? Do your family/friends encourage you to plan and budget food purchases?" (Never = 1; Rarely = 2; Occasionally = 3; Often = 4; Always = 5)	3.5506 (0.8684)	3.5404 (0.8622)	3.5612 (0.8803)	3.5516 (0.8651)
Food Waste	"Producing food is complex and difficult; conserving food saves substantial money; it is	3.8829 (0.6624)	3.8423 (0.6828)	3.8895 (0.6783)	3.9214 (0.6199)

Variable	Definition and Coding	Full Sample	Health Information Group	Sustainability Information Group	No-Information Control Group
Perceived Behaviors	difficult to budget portions when purchasing food and vegetables.” (Strongly disagree = 1; Disagree = 2; Neutral = 3; Agree = 4; Strongly agree = 5)				
1 Control					
	Sample Size	1469	528	465	476

Note: Values in parentheses represent standard deviations.

4.2 Effects of Information Interventions on Consumer Preferences

After describing the basic characteristics of the sample, we further empirically tested the average treatment effects of information interventions on consumer preferences using the econometric models. The models were estimated in RStudio, and the results are presented in Table 3. The regression results indicate that the coefficients for the low-loss label are positive across all three groups, although their significance and magnitude vary substantially. Specifically, in the control group without any information intervention (Model 3), the coefficient for the low-loss label is positive but not statistically significant. In contrast, in the health and sustainability information intervention groups (Models 1-2), the preference becomes statistically significant, and the corresponding willingness-to-pay estimates increase noticeably, with the effect of the health information intervention being the most pronounced. The coefficient in the health information group is significantly positive at the 1% level. The impact of the information interventions is not limited to the core label but also significantly moderates consumers' evaluations of specific food loss reduction technologies. Consumers in the health information group exhibit significant positive preferences for products with selenium-enriched certification (0.0889***) and national geographic indication certification (0.0829***), suggesting that health information may activate attention to related attributes such as nutrition and quality. Consumers in the sustainability information group show strong and consistent preferences for specific sustainable technologies, including mechanized production equipment (0.0779**), sealed bag packaging (0.1340**), and cold chain storage facilities (0.1155***), indicating that sustainability information successfully guides consumers to recognize and value the technologies applied during production and storage. In contrast,

consumers in the no-information control group do not display significant preferences for most technological attributes.

Overall, all three models (Models 1-3) exhibit good fit. Price is a significant determinant of consumer purchasing decisions (Sigurdsson et al., 2020), with a consistently negative coefficient, in line with consumer demand theory. The estimated coefficient for the “none of these” option is significantly negative, indicating that respondents are more likely to choose among the given rice alternatives rather than opt out entirely. That is, when presented with three options in the choice set, consumers prefer selecting either Rice A or Rice B rather than choosing “none of these,” confirming the rationality of the experimental design. Moreover, the model fit for both information intervention groups is slightly higher than that of the control group, indirectly supporting the notion that incorporating information variables enhances the explanatory power of the models.

Table 3. Baseline Multinomial Logit Regression Results

Variable	(1)	(2)	(3)
	Health Information Group	Sustainability Information Group	No-Information Control Group
Food Loss Reduction Label (High-loss)	-0.0551 (0.0408)	0.0147 (0.0422)	0.0046 (0.0463)
Food Loss Reduction Label (Low-loss)	0.1163*** (0.0384)	0.1015** (0.0413)	0.0654 (0.0401)
Production-stage Loss Reduction Technology (Mechanized Equipment)	0.0125 (0.0413)	0.0779** (0.0379)	0.0074 (0.0387)
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.0314 (0.0385)	0.0462 (0.0375)	0.0160 (0.0371)
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	0.0082 (0.0326)	0.1340*** (0.0364)	0.0540 (0.0359)
Storage-stage Loss Reduction Technology (Cold Chain Storage)	-0.0505 (0.0357)	0.1155*** (0.0382)	-0.0328 (0.0378)
Selenium-enriched Certification	0.0889*** (0.0335)	0.0337 (0.0370)	0.0732* (0.0378)
National Geographic Indication Certification	0.0829*** (0.0319)	0.0080 (0.0336)	-0.0068 (0.0352)
Price	-0.0376*** (0.0055)	-0.0340*** (0.0064)	-0.0504*** (0.0055)
None of These	-1.6668*** (0.1012)	-1.7503*** (0.1166)	-1.9109*** (0.1061)
Sample Size	6336	5580	5712
Pseudo R ²	0.1433	0.1657	0.1637
Log Likelihood (final)	-5953.09	-5104.32	-5237.87
AIC	11926.18	10228.64	10495.73
BIC	11993.72	10294.91	10562.23

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

To provide a more intuitive interpretation of the economic significance and enable cross-group comparisons, this study further estimated consumers' willingness-to-pay (WTP) and confidence intervals for each attribute level based on the multinomial logit model results. Following Krinsky and Robb's (1986) bootstrap method, 1,000 parameter simulations were generated using the rmvnorm function. The results are presented in Table 4. The findings indicate that both health and sustainability information interventions significantly increase consumers' WTP for low-loss rice labels, turning previously statistically insignificant preferences into significant positive valuations, with WTP levels increasing by approximately 130%. Moreover, the two types of information operate through distinct pathways. Health information increases WTP through nutritional and quality attributes, with consumers exhibiting significant positive WTP for selenium-enriched certification (WTP = 2.3867) and national geographic indication certification (WTP = 2.2027). In contrast, sustainability information increases WTP via technological attributes, with the highest and statistically significant WTP observed for sealed bag packaging (WTP = 3.9389), cold chain storage facilities (WTP = 3.4622), and mechanized production equipment (WTP = 2.3585).

Table 4. Consumers' Willingness-to-Pay for Rice Attributes

Attribute	Health Information Group	Sustainability Information Group	No-Information Control Group
Food Loss Reduction Label (High-loss)	-1.4810 [-3.4036, 0.2986]	0.4174 [-1.6889, 2.5853]	0.0816 [-1.4699, 1.5988]
Food Loss Reduction Label (Low-loss)	3.0956 [1.3989, 4.9574]	3.0078 [0.8991, 5.4667]	1.3303 [-0.0101, 2.5811]
Production-stage Loss Reduction Technology (Mechanized Equipment)	0.3892 [-1.4161, 2.3681]	2.3585 [0.5185, 4.8063]	0.1930 [-1.1050, 1.5288]
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.7684 [-2.5183, 0.9440]	1.3714 [-0.3239, 3.3632]	0.3480 [-0.8878, 1.5622]
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	0.2164 [-1.1398, 1.5931]	3.9389 [2.1364, 6.4586]	1.1341 [-0.1261, 2.2511]
Storage-stage Loss Reduction Technology (Cold Chain Storage)	-1.3421 [-2.9586, 0.2536]	3.4622 [1.4223, 6.3134]	-0.6522 [-1.8314, 0.6623]
Selenium-enriched Certification	2.3867 [0.8838, 4.0516]	0.9777 [-0.7897, 2.9664]	1.4532 [0.2232, 2.7061]
National Geographic Indication Certification	2.2027 [0.7566, 3.7210]	0.2344 [-1.5355, 1.8401]	-0.1223 [-1.4260, 0.9317]

Note: Values in brackets represent 95% confidence intervals.

4.3 Effects of Individual Attributes on Heterogeneity in Consumer Preferences

To examine the sources of heterogeneity in consumer preferences, interaction terms between respondents' demographic characteristics and rice attributes were incorporated into the baseline multinomial logit model (Table 3). The results are presented in Table 5. In the health information intervention group (Model 4), heterogeneity in consumer preferences is primarily observed along the dimensions of income and age. Income has a highly significant effect on consumer demand (Falkinger & Zweimüller, 1997), with high-income consumers exhibiting significantly stronger preferences for the low-loss label (0.1796^{***}), selenium-enriched certification (0.1407^{**}), and national geographic indication certification (0.1368^{**}). Older consumers show significantly stronger preferences for selenium-enriched certification (0.0074^{***}) and national geographic indication certification (0.0059^{**}). Notably, these positive relationships are reversed in the no-information control group (Model 6), where older consumers demonstrate negative or indifferent preferences. Health information effectively alters previously indifferent attitudes among older consumers, transforming them into active evaluators of health- and quality-related attributes. In the sustainability information intervention group (Model 5), consumers from larger households exhibit stronger preferences for cold chain storage technology (0.0680^{**}), which relates to safety and stability in storage and distribution. This may reflect the greater concern of larger households for food security and supply stability, with the sustainability information highlighting supply chain protection and loss reduction resonating with these concerns. High-income consumers also show a significant positive preference for the low-loss label (0.1011^{*}), but the magnitude is substantially smaller than in the health information group. Additionally, the moderating effects of sustainability information on preferences for attributes such as selenium-enriched certification are not significant, indicating that sustainability information is less effective than health information at eliciting high WTP among high-income consumers.

By contrast, in the no-information control group, differences in consumer preferences are primarily driven by inherent socioeconomic characteristics. Education emerges as a key factor influencing preference heterogeneity, with more highly educated consumers exhibiting significantly stronger preferences for the low-loss label

(0.1012^{**}) and intelligent production technology (0.0771^{*}). This suggests that, in the absence of external information guidance, understanding technologically sophisticated or novel product attributes presents a cognitive barrier, making education the main variable differentiating consumers' comprehension and acceptance. Older consumers show negative preferences for selenium-enriched and geographic indication certifications, and income does not significantly affect preferences for the low-loss label. This indicates that, without information interventions, income differences do not translate into higher WTP for this attribute.

Table 5. Multinomial Logit Regression Results with Interactions between Rice Attributes and Individual Characteristics

Variable	(4)	(5)	(6)
	Health Information Group	Sustainability Information Group	No-Information Control Group
Low-loss Label × Gender	0.0124 (0.0714)	-0.0655 (0.0749)	-0.0716 (0.0729)
Intelligent Production × Gender	-0.0237 (0.0647)	-0.0182 (0.0646)	-0.0005 (0.0627)
Cold Chain Storage × Gender	-0.0783 (0.0681)	0.0265 (0.0734)	-0.0069 (0.0729)
Selenium-enriched Certification × Gender	-0.1058 (0.0728)	-0.0632 (0.0814)	-0.1070 (0.0767)
National Geographic Indication Certification × Gender	-0.1010 (0.0653)	-0.0095 (0.0680)	-0.0472 (0.0729)
Low-loss Label × Age	0.0039 (0.0025)	-0.0008 (0.0034)	-0.0019 (0.0031)
Intelligent Production × Age	0.0023 (0.0025)	-0.0001 (0.0026)	-0.0019 (0.0029)
Cold Chain Storage × Age	-0.0036 (0.0026)	0.0007 (0.0027)	-0.0042 (0.0029)
Selenium-enriched Certification × Age	0.0074 ^{***} (0.0027)	-0.0018 (0.0032)	-0.0113 ^{***} (0.0037)
National Geographic Indication Certification × Age	0.0059 ^{**} (0.0025)	-0.0028 (0.0026)	-0.0070 ^{**} (0.0035)
Low-loss Label × Education	0.0184 (0.0398)	0.0236 (0.0427)	0.1012 ^{**} (0.0494)
Intelligent Production × Education	-0.0615 (0.0427)	-0.0040 (0.0403)	0.0771 [*] (0.0444)
Cold Chain Storage × Education	-0.0440 (0.0411)	-0.0264 (0.0442)	-0.0334 (0.0480)
Selenium-enriched Certification × Education	0.0678 (0.0427)	0.0031 (0.0498)	0.0027 (0.0546)
National Geographic Indication Certification × Education	0.0400 (0.0371)	0.0068 (0.0394)	-0.0415 (0.0500)
Low-loss Label × Household Size	0.0188 (0.0315)	0.0187 (0.0306)	-0.0120 (0.0296)
Intelligent Production × Household Size	0.0277 (0.0296)	0.0288 (0.0303)	-0.0280 (0.0244)
Cold Chain Storage × Household Size	-0.0397 (0.0273)	0.0680 ^{**} (0.0323)	-0.0401 (0.0308)
Selenium-enriched Certification × Household Size	0.0714 ^{**} (0.0312)	-0.0074 (0.0345)	0.0223 (0.0310)
National Geographic Indication Certification × Household Size	0.0242 (0.0286)	0.0060 (0.0283)	0.0223 (0.0297)
Low-loss Label × Income	0.1796 ^{***} (0.0638)	0.1011 [*] (0.0614)	0.0725 (0.0583)

Variable	(4)	(5)	(6)
	Health Information Group	Sustainability Information Group	No-Information Control Group
Intelligent Production × Income	0.0677 (0.0618)	0.0356 (0.0513)	-0.0929* (0.0532)
Cold Chain Storage × Income	0.0910 (0.0574)	0.0023 (0.0632)	0.0053 (0.0607)
Selenium-enriched Certification × Income	0.1407** (0.0665)	-0.0315 (0.0666)	-0.0239 (0.0566)
National Geographic Indication Certification × Income	0.1368** (0.0603)	-0.0008 (0.0543)	0.0462 (0.0569)
Sample Size	6336	5580	5712
Pseudo R ²	0.1458	0.1632	0.1649
Log Likelihood (final)	-5910.62	-5094.72	-5205.62
AIC	11891.24	10259.44	10481.24
BIC	12127.63	10491.38	10714.01

Note: Income is log-transformed.

4.4 Heterogeneity in Consumer Preferences by Psychological Cognition

Beyond observable demographic characteristics, consumers' pre-existing psychological cognitions and attitudes constitute deeper drivers of decision-making. This study further examines whether the effects of information interventions vary according to consumers' internal psychological states, with results presented in Table 6. In the health information intervention group, consumers exhibit significant positive preferences for the low-loss label regardless of their attitudinal levels (High-attitude: 0.1286**; Low-attitude: 0.1013*). This suggests that health-focused information has broad applicability. By activating consumers' egoistic motives, which pertain to personal nutrition security and health risk, health information effectively increases WTP across groups with varying value orientations. The coefficient for the high-attitude group is slightly higher than that for the low-attitude group, indicating that health information has a greater effect on consumers with stronger pre-existing attitudes toward food conservation, possibly due to a reinforcing effect between existing values and the information.

In the sustainability information intervention group, the heterogeneity of the intervention effect is more pronounced. Only high-attitude consumers show a significant positive preference for the low-loss label (0.1418*), while the preference of low-attitude consumers is not significant. Sustainability information activates altruistic motives, emphasizing the contribution of food loss reduction to social and environmental public goods. High-attitude consumers, who already hold positive

values toward food conservation, resonate with this information, resulting in a significant enhancement of their preferences. In contrast, low-attitude consumers, lacking such internal value foundations, respond weakly to altruistic information.

In the no-information control group, only high-attitude consumers display a significant preference for the low-loss label (0.1215**), while the low-attitude group's preference remains non-significant. This indicates that, in the absence of external information guidance, spontaneous demand for low-loss products primarily originates from consumers with strong intrinsic values toward food conservation.

Table 6. Regression Results for Heterogeneity in Consumer Preferences by Food Conservation Attitudes

Variable	(7)	(8)	(9)	(10)	(11)	(12)
	Health Information Group		Sustainability Information Group		No-Information Control Group	
	High-attitude	Low-attitude	High-attitude	Low-attitude	High-attitude	Low-attitude
Food Loss Reduction Label (High-loss)	-0.0944* (0.0560)	-0.0034 (0.0592)	-0.0153 (0.0559)	0.0584 (0.0649)	-0.0194 (0.0651)	0.0317 (0.0656)
Food Loss Reduction Label (Low-loss)	0.1286** (0.0532)	0.1013* (0.0555)	0.1418* (0.0554)	0.0413 (0.0611)	0.1215** (0.0565)	-0.0060 (0.0556)
Production-stage Loss Reduction Technology (Mechanized Equipment)	0.0532 (0.0557)	-0.0412 (0.0615)	0.1172** (0.0501)	0.0164 (0.0573)	0.0436 (0.0554)	-0.0409 (0.0527)
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.0360 (0.0514)	-0.0253 (0.0584)	0.0900* (0.0500)	-0.0219 (0.0570)	0.0718 (0.0519)	-0.0558 (0.0527)
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	-0.0061 (0.0438)	0.0263 (0.0489)	0.0749 (0.0460)	0.2151*** (0.0592)	0.0692 (0.0472)	0.0417 (0.0553)
Storage-stage Loss Reduction Technology (Cold Chain Storage)	-0.0435 (0.0485)	-0.0599 (0.0526)	0.1024** (0.0497)	0.1344** (0.0605)	-0.0697 (0.0505)	0.0134 (0.0565)
Selenium-enriched Certification	0.0934** (0.0453)	0.0818* (0.0500)	-0.0013 (0.0508)	0.0785 (0.0541)	0.0698 (0.0517)	0.0817 (0.0552)
National Geographic Indication Certification	0.0805* (0.0428)	0.0849* (0.0476)	0.0327 (0.0421)	-0.0229 (0.0559)	0.0478 (0.0471)	-0.0718 (0.0530)
Price	-0.0426*** (0.0081)	-0.0310*** (0.0071)	-0.0412*** (0.0092)	-0.0245*** (0.0089)	-0.0604*** (0.0080)	-0.0389*** (0.0077)
None of These	-1.8159*** (0.1311)	-1.4864*** (0.1552)	-1.8491*** (0.1448)	-1.6207*** (0.1914)	-2.0448*** (0.1449)	-1.7600*** (0.1548)
Sample Size	3576	2760	3288	2292	3192	2520

	(7)	(8)	(9)	(10)	(11)	(12)
Variable	Health Information Group		Sustainability Information Group		No-Information Control Group	
	High-attitude	Low-attitude	High-attitude	Low-attitude	High-attitude	Low-attitude
Pseudo R ²	0.1603	0.1208	0.1746	0.1530	0.1851	0.1385
Log Likelihood (final)	-3288.75	-2655.88	-2971.41	-2122.77	-2847.84	-2374.98
AIC	6597.50	5331.76	5962.81	4265.53	5715.68	4769.97
BIC	6659.32	5390.99	6023.79	4322.90	5776.36	4828.29

Table 7 shows that in the health information intervention group, both high- and low-efficacy consumers exhibit significant positive preferences for the low-loss label (High-efficacy: 0.1268^{**}; Low-efficacy: 0.1073^{*}), with the high-efficacy group displaying slightly stronger preference intensity. This indicates that information emphasizing private health benefits has broad acceptability and can effectively increase consumers' willingness-to-pay. In contrast, the sustainability information intervention group exhibits a markedly different pattern. Low-efficacy consumers show a significant and stronger preference for the low-loss label (0.1394^{**}), whereas the high-efficacy group's preference is not significant. This suggests that sustainability information, which highlights social benefits, primarily persuades consumers who initially hold skeptical or uncertain beliefs about technological effectiveness. Such information may effectively alter the prior perceptions of low-efficacy consumers, compensating for their knowledge gaps and significantly enhancing their preferences. In the no-information control group, neither high- nor low-efficacy consumers demonstrate significant preferences for the low-loss label. This indicates that, in the absence of external information guidance, consumers' intrinsic knowledge and cognitive abilities alone are insufficient to generate stable and significant WTP for low-loss labels, further underscoring the necessity of information interventions.

Table 7. Regression Results for Heterogeneity in Consumer Preferences by Loss-Reduction Response Efficacy

	(13)	(14)	(15)	(16)	(17)	(18)
Variable	Health Information Group		Sustainability Information Group		No-Information Control Group	
	High-efficacy	Low-efficacy	High-efficacy	Low-efficacy	High-efficacy	Low-efficacy
Food Loss Reduction Label (High-loss)	-0.0458 (0.0576)	-0.0664 (0.0578)	-0.0059 (0.0570)	0.0372 (0.0634)	0.0639 (0.0653)	-0.0583 (0.0662)
Food Loss Reduction Label	0.1268 ^{**} (0.0529)	0.1073 [*] (0.0560)	0.0664 (0.0555)	0.1394 ^{**} (0.0620)	0.0889 (0.0562)	0.0455 (0.0575)

	(13)	(14)	(15)	(16)	(17)	(18)
Variable	Health Information Group		Sustainability Information Group		No-Information Control Group	
	High- efficacy	Low- efficacy	High- efficacy	Low- efficacy	High- efficacy	Low- efficacy
(Low-loss)						
Production-stage Loss Reduction Technology (Mechanized Equipment)	-0.0596 (0.0587)	0.0939 (0.0580)	0.0755 (0.0505)	0.0816 (0.0565)	-0.0641 (0.0516)	0.0853 (0.0586)
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.0575 (0.0545)	-0.0019 (0.0545)	0.1199** (0.0507)	-0.0395 (0.0551)	0.0053 (0.0494)	0.0235 (0.0568)
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	0.0176 (0.0454)	0.0002 (0.0472)	0.1615*** (0.0501)	0.1034** (0.0529)	0.0552 (0.0498)	0.0544 (0.0528)
Storage-stage Loss Reduction Technology (Cold Chain Storage)	0.0097 (0.0496)	-0.1174 (0.0517)	0.1525*** (0.0526)	0.0738 (0.0556)	-0.0315 (0.0507)	-0.0387 (0.0572)
Selenium- enriched Certification National	0.1168*** (0.0445)	0.0603 (0.0509)	0.0488 (0.0460)	0.0154 (0.0600)	0.0785 (0.0531)	0.0698 (0.0544)
Geographic Indication Certification	0.0924** (0.0433)	0.0767* (0.0476)	0.0139 (0.0431)	-0.0005 (0.0532)	-0.0035 (0.0476)	-0.0099 (0.0526)
Price	-0.0207*** (0.0066)	-0.0569*** (0.0092)	-0.0390*** (0.0079)	-0.0287*** (0.0104)	-0.0297*** (0.0069)	-0.0730*** (0.0089)
None of These	-1.6228*** (0.1399)	-1.7239*** (0.1481)	-1.8353*** (0.1690)	-1.6642*** (0.1626)	-1.8586*** (0.1620)	-1.9771*** (0.1415)
Sample Size	3276	3060	2988	2592	2892	2820
Pseudo R ²	0.1492	0.1408	0.1774	0.1511	0.1653	0.1667
Log Likelihood (final)	-3052.19	-2878.49	-2690.19	-2407.27	-2641.85	-2571.59
AIC	6124.38	5776.99	5400.38	4834.55	5303.69	5163.18
BIC	6185.32	5837.25	5460.40	4893.15	5363.39	5222.62

4.5 Robustness Checks

To further assess the robustness of the estimation results, the baseline multinomial logit models were re-estimated using a Random Parameter Logit (RPL) model. The RPL estimation results are presented in Table 8, with 500 draws used for simulation. The results indicate that the signs and relative magnitudes of the core coefficients are largely consistent with those in the baseline models reported in Table 3. This suggests that the baseline regression results are not substantively affected by the change in model specification, providing evidence for the reliability and robustness of the parameter estimates.

Table 8. Estimation Results of the Random Parameter Logit (RPL) Model (interNDraws = 500)

Variable	(19)	(20)	(21)	(22)	(23)	(24)
	Health Information Group		Sustainability Information Group		No-Information Control Group	
	RPL(Coeff)	RPL (SD)	RPL(Coeff)	RPL (SD)	RPL(Coeff)	RPL (SD)
Food Loss Reduction Label (High-loss)	-0.0563 (0.0702)	0.4498*** (0.0483)	-0.0004 (0.0215)	0.3520*** (0.1194)	0.0044 (0.0043)	0.5301*** (0.0764)
Food Loss Reduction Label (Low-loss)	0.1825*** (0.0472)	-0.5049*** (0.0435)	0.1256*** (0.0328)	0.3454*** (0.1075)	0.0790 (0.0517)	-0.3334*** (0.1004)
Production-stage Loss Reduction Technology (Mechanized Equipment)	0.0014 (0.0100)	0.1985 (0.1829)	0.1395*** (0.0540)	-0.0489 (0.1690)	0.0037** (0.0017)	0.0394*** (0.0119)
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.0658 (0.0424)	-0.1305 (0.1610)	0.0804 (0.0582)	0.0353 (1.5371)	0.0132*** (0.0016)	0.0373 (0.1694)
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	-0.0031 (0.0398)	-0.0224 (0.1528)	0.2035*** (0.0028)	0.0025 (0.0121)	0.0393 (0.1080)	0.0520*** (0.0091)
Storage-stage Loss Reduction Technology (Cold Chain Storage)	-0.0591 (0.0490)	0.0272*** (0.0038)	0.1805*** (0.0462)	-0.0204 (0.0787)	-0.0475 (0.1229)	-0.0182** (0.0072)
Selenium-enriched Certification	0.0949** (0.0477)	0.2411** (0.1229)	0.0604*** (0.0193)	0.4068*** (0.0993)	0.1073** (0.0534)	0.3920*** (0.0943)
National Geographic Indication Certification	0.0764 (0.0679)	0.3433*** (0.0834)	0.0332 (0.0311)	-0.3340*** (0.0790)	-0.0246 (0.0166)	0.4060*** (0.0837)
Price	-0.0600*** (0.0091)	0.1589*** (0.0124)	-0.0715*** (0.0120)	0.2077*** (0.0018)	-0.0793*** (0.0100)	0.1386*** (0.0116)
None of These	-3.2897*** (0.1803)	2.3452*** (0.1473)	-3.8960*** (0.6091)	3.3382*** (0.4698)	-3.5477*** (0.2350)	2.3067*** (0.2393)
Sample Size	6336		5580		5712	
Pseudo R ²	0.2400		0.2797		0.2436	
Log Likelihood (final)	-5270.55		-4395.39		-4726.8	
AIC	10581.09		8830.78		9493.59	
BIC	10716.17		8963.32		9626.6	

Building on this, the sensitivity of the RPL model estimates to the number of simulation draws was further examined. The number of draws was increased from 500 to 1,000, and the model was re-estimated, with results presented in Table 9. The findings indicate that the two estimations are highly similar, showing no substantial variation due to the increased number of simulations draw. This demonstrates that the RPL model estimates are stable and not sensitive to the choice of simulation draws, providing further evidence for the robustness of the study's main conclusions.

Table 9. Estimation Results of the Random Parameter Logit (RPL) Model (interNDraws = 1000)

	(25)	(26)	(27)	(28)	(29)	(30)
Variable	Health Information Group		Sustainability Information Group		No-Information Control Group	
	RPL(Coeff)	RPL(SD)	RPL(Coeff)	RPL (SD)	RPL(Coeff)	RPL (SD)
Food Loss Reduction Label (High-loss)	-0.0582 (0.0429)	0.4693*** (0.0771)	-0.0101 (0.0078)	-0.3463*** (0.1243)	0.0058 (0.9421)	0.5333*** (0.0832)
Food Loss Reduction Label (Low-loss)	0.1811*** (0.0430)	0.4760*** (0.0949)	0.1299*** (0.0474)	0.4028*** (0.1016)	0.0801 (0.0567)	-0.3410*** (0.1020)
Production-stage Loss Reduction Technology (Mechanized Equipment)	0.0007*** (0.0002)	-0.1017 (0.0760)	0.1419** (0.0613)	-0.0134 (0.0176)	0.0059 (0.3089)	0.0125 (0.0832)
Production-stage Loss Reduction Technology (Intelligent Production Technology)	-0.0654 (0.0620)	0.0720 (0.1733)	0.0786 (0.0616)	-0.0141 (0.0256)	0.0122 (2.0059)	0.0066 (0.3525)
Storage-stage Loss Reduction Technology (Sealed Bag Packaging)	-0.0020 (0.0015)	-0.0127* (0.0075)	0.2084*** (0.0599)	0.0592 (3.8751)	0.0386 (0.0280)	-0.0182*** (0.0024)
Storage-stage Loss Reduction Technology (Cold Chain Storage)	-0.0588 (0.0656)	-0.0021* (0.0012)	0.1773** (0.0736)	-0.1117 (0.1858)	-0.0489 (0.0437)	-0.1220 (0.8141)
Selenium-enriched Certification	0.0939* (0.0518)	0.2184* (0.1301)	0.0638 (0.1144)	0.4101*** (0.0978)	0.1120 (0.0822)	0.3655*** (0.1077)
National Geographic Indication Certification	0.0806** (0.0324)	0.3531*** (0.0768)	0.0394 (0.0538)	0.3832*** (0.0722)	-0.0261 (0.0316)	0.3950*** (0.0710)
Price	-0.0596*** (0.0095)	0.1585*** (0.0125)	-0.0701*** (0.0126)	0.2150*** (0.0192)	-0.0779*** (0.0125)	0.1413*** (0.0187)
None of These	-3.2424*** (0.1979)	2.2281*** (0.1822)	-3.9777*** (0.8954)	3.0384*** (0.5284)	-3.5532*** (1.3142)	2.2624** (1.0417)
Sample Size	6336		5580		5712	
Pseudo R ²	0.2400		0.2812		0.2437	
Log Likelihood (final)	-5270.20		-4386.38		-4725.94	
AIC	10580.40		8812.76		9491.87	
BIC	10715.48		8945.3		9624.88	

5 Conclusions and Policy Implications

Based on survey data from 1,469 rice consumers, this study employed randomized information interventions and discrete choice experiments to systematically compare the effects of health and sustainability information on consumers' preferences for low-loss rice labels. It further investigated how consumers' individual characteristics and psychological cognitions moderate these effects. The main findings are as follows.

First, information interventions are an effective strategy for guiding consumers' attention to and valuation of food loss reduction attributes, with significant differences in the pathways through which health and sustainability information operate. Baseline

regression results indicate that, compared to the no-information control group, both health and sustainability information interventions significantly increase consumers' preferences and willingness-to-pay for low-loss rice labels. However, the mechanisms differ: health information interventions increase WTP for health-related attributes—such as selenium-enriched certification and national geographic indication certification—by activating consumers' attention to nutrition and quality, whereas sustainability information interventions enhance recognition of technological value, significantly increasing consumers' preferences for specific loss-reduction technologies, including mechanized production, sealed bag packaging, and cold chain storage.

Second, consumers' individual characteristics significantly moderate the effects of information interventions, exhibiting heterogeneity across information contexts. In the health information group, high-income consumers display stronger preferences for the low-loss label, selenium-enriched certification, and geographic indication certification, while older consumers show significantly stronger preferences for health- and quality-related attributes. In the sustainability information group, consumers from larger households exhibit stronger preferences for cold chain storage technology, and high-income consumers show a weaker preference for the low-loss label compared with the health information group. In the no-information control group, education emerges as the key factor driving preference heterogeneity: more highly educated consumers display significantly stronger preferences for low-loss labels.

Third, the effects of information interventions on consumer preferences vary according to psychological cognition. Regarding food conservation attitudes, health information effectively increases WTP across consumers with both high and low attitudinal levels, whereas sustainability information significantly affects only high-attitude consumers. Regarding perceived efficacy in loss reduction, health information effectively enhances preferences for both high- and low-efficacy groups, while sustainability information exerts stronger persuasive effects on low-efficacy consumers. By contrast, in the no-information control group, neither psychological variable significantly moderates preferences, further highlighting the necessity of information interventions.

Based on these findings, the following policy recommendations are proposed to enhance the food loss reduction policy system and guide consumer behavior. First, establish standardized, transparent, and credible food loss reduction labels. The government should implement national standards and certification procedures, including third-party verification and public disclosure, to ensure label authenticity and reliability. Misleading or false labels should be strictly penalized, thereby building consumer trust and enabling labels to serve as effective tools for consumers to participate in socially responsible food loss reduction. Second, implement differentiated information intervention strategies according to target groups and policy objectives. For health-conscious middle-aged and older consumers, interventions should emphasize the health benefits of food loss reduction, such as nutrient retention and avoidance of safety risks. For socially responsible younger consumers, interventions should highlight the societal value of loss-reduction technologies, including ensuring supply chain stability and promoting sustainable resource use. Furthermore, enterprises should be encouraged to integrate health and sustainability information in product packaging and e-commerce platforms to guide consumers toward comprehensive understanding and stable preferences for low-loss products.

Despite its contributions, this study has several limitations that should be acknowledged. First, this study conducted a randomly sampled online questionnaire survey through the Questionnaire Star website. The sample is relatively young and highly educated, which deviates to some extent from the overall demographic structure of the national population. Although online surveys facilitate rapid data collection and reduce survey costs, caution is needed when generalizing the results to broader populations. Future research could adopt a combination of offline and online methods, or conduct stratified sampling targeting specific populations. Second, this study provided consumers with a one-time health or sustainability information intervention only before the discrete choice experiment, without examining the duration and decay patterns of the information intervention effects. Consumer preferences may weaken over time or require repeated information stimuli to be maintained. Future research could design multi-round information interventions or longitudinal tracking

experiments to assess long-term information effects and their dynamic changes. Third, the discrete choice experiment measures consumers stated preferences in hypothetical scenarios rather than their actual purchasing behavior in real markets. Although the experimental design included an opt-out option (“none of these”) to enhance realism, consumers may overstate their willingness to pay in the absence of actual payment pressure. Future research could combine real market experiments (e.g., shelf experiments, online sales data) or incentive-compatible auction experiments to improve external validity. Fourth, this study treated health information and sustainability information separately, without examining the effects of providing both types of information simultaneously (i.e., mixed information intervention). In reality, consumers may be exposed to both health and sustainability information at the same time, and the two may have synergistic or antagonistic effects.

CRedit authorship contribution statement

Shiyu Liu: Writing original draft, Data curation, Methodology, Software. **Jie Lyu:** Conceptualization, Funding acquisition, Supervision. **Guanqiu Yin:** Writing original draft. **Jian Zhuang:** Conceptualization, Funding acquisition, Supervision. **Junyan Zhang:** Methodology, Validation, Writing- Reviewing and Editing, Funding acquisition, Supervision.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data and analysis code that support the findings of this study are available in Figshare at <https://doi.org/10.6084/m9.figshare.33885364>. Access to the de-identified dataset is restricted to editors, reviewers, and authorized researchers due to privacy and confidentiality restrictions. No other restrictions apply.

Ethics Approval

This study was approved by the Ethics Review Committee of Shenyang Agricultural University (Approval No.: SYAU2026091203). All procedures performed in studies involving human participants were in accordance with the 1964 Helsinki Declaration and its later amendments. All participants provided informed consent. We confirm that no participants under 16 years of age were involved in this study; therefore, parental or guardian consent was not required.

Consent to Participate

Informed consent was obtained from all individual participants included in the study.

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