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RESEARCH

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Which food date label brings us the most excellent opportunity to reduce food waste? Evidence from a quasi-natural intervention experiment in urban China

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Abstract

Since various food date labeling (FDL) systems exist worldwide, consumers' confusion and misunderstanding of FDL are unavoidable, which may result in a large amount of food waste at the consumer stage. To what extent consumers' FDL cognition affects their food waste behaviors and intentions has yet been well documented. Using the online survey data ($N=7830$, two-period panel) from China, we examine the relationship between FDL cognition and food waste behaviors, quantify the resulting food waste amount, and use difference-in-differences models to evaluate the net effect of the information intervention. The results show that only 6.46% of urban consumers in China have correct FDL cognition, and this cognition has a significant relationship with their food waste behaviors. The FDL information intervention significantly improves consumers' FDL cognition and corrects their food waste intention, and the quality guaranteed date label has the most significant potential for reducing food waste, which is the most widely used FDL type in China currently. Based on the findings, strengthening the localized and targeted FDL popularization is a practical and promising way to reduce food waste, especially the most potential label type.

Keywords: SDG12.3, Sustainable consumption behavior, Food date labeling (FDL), Consumer cognition, Experimental economics, Difference-in-differences (DID)

Introduction

Food loss and waste have recently received growing interest from the public, politicians, and academic researchers from various disciplinary fields (Beretta et al. 2013; Davenport et al. 2019; De Gorter et al. 2021; Schmidt 2016). Available estimates from the Food and Agriculture Organization of the United Nations (FAO) (2011) show that food loss and waste worth about \$940 billion each year globally throughout the entire food supply chain, and between one-third and one-half of the produced food (approximately 1.3 billion tons per year) is being lost in the early stages of the food supply chain or wasted at the consumer stage. Given such considerable food waste, severe environmental, social, and economic consequences have been detected throughout the whole food supply

chain (Bellemare et al. 2017; Block et al. 2022; Patra et al. 2022). In particular, the protracted COVID-19 pandemic, climate shocks, and frequent conflicts and turbulences, such as the war in Ukraine, have increased the number of hungry people worldwide by more than 122 million since 2019 (FAO 2023). The issue of minimizing food waste could promote sustainable management and utilization of resources, mitigate the great contradiction with hunger, and benefit present and future generations (Poore and Nemecek 2018; World Food Programme 2023).

Household food waste (HFW) is a significant source of food loss and waste along the food supply chain in many developed countries (Wallnoefer et al. 2024; Secondi et al. 2015), and food waste due to food date labeling (FDL) is a growing concern (Neubig and Roosen 2024; Ray et al. 2024; Wilson and Miao 2025). More than 90% of Americans may throw away food prematurely because they misunderstand date labels as the indicators of food safety (Natural Resources Defense Council 2012), which brings about 20% of food waste in the consumer stage in the United States of America.¹ Contrary to the traditional view that food waste occurs mainly in developed economies, with the growth of per capita income in transition economies, there is also much food waste (United Nations Environment Programme 2021) while the extent of food waste due to food date labels is unclear.

Regarding the determinants of HFW, many existing studies investigate various factors from different perspectives, such as social (Gatersleben et al. 2019), economic (Aschemann-Witzel et al. 2017), and consumer characteristics (Aka and Buyukdag 2021; Garcia-Herrero et al. 2018). However, there are relatively few studies based on actions to reduce consumers' food waste. Although some scholars have researched the impact of information on consumers' food waste behavior and intention (Dai and Gong 2024; Zheng et al. 2023), less attention has been paid to the impact of food labeling information on food waste, especially the FDL, which serves as a primary carrier for food production enterprises to disclose their product's safety or quality information (Hall-Phillips and Shah 2017). Internationally, different countries have different FDL regulations, and we summarize the representatives detailed in Table S1.

Due to the complexity of various labeling systems, most labels can hardly guide consumers' behavior but merely serve as legal disclaimers (Malek et al. 2020), and consumers are faced with severe information asymmetry in understanding the FDL in the market (Hall-Phillips and Shah 2017; Kavanaugh and Quinlan 2020). Many food manufacturers use date labels to indicate food quality and freshness to consumers rather than product safety information from a microbial perspective (Newsome et al. 2014). However, consumers do not understand how these different labels relate to food safety or quality and why they differ among foods. As many as 50% do not know the differences between best before, sell-by, and use-by dates (Milne 2012). They often mistakenly believe that FDL is intended to convey food safety information and throw away a large amount of safe, healthy, and high-quality food to avoid foodborne diseases (Hall-Phillips and Shah 2017; Newsome et al. 2014). There is a growing demand to develop effective messages that can reduce food waste (Zheng et al. 2023), and FDL may be an essential

¹ <https://www.fda.gov/media/125114/download?attachment>

opportunity (Campbell and Feldpausch 2022) while we know little about this information asymmetry (Stancu and Lähteenmäki 2022). The existing studies on this issue are almost all from developed countries, and there is a lack of data and evidence from transition economies. China, in particular, the most representative transition economy, is undergoing rapid changes in diet and urbanization, which is a potentially vital area for reducing global food waste (Xue et al. 2017), and the current situation of this issue is unknown.

To address the research gaps, in this study, we take Chinese consumers, the consumer representative of transition economies, as our research object, quantitatively demonstrate the consumers' cognitive status of FDL, examine the causal relationship between consumer labeling cognition and food waste behavior and quantify the amount of food waste due to misunderstanding initiatively. We further explore the effects of information intervention on labeling cognition, food waste intention, and heterogeneity. Considering that the pressure on resources and the environment caused by food waste has become a significant obstacle to sustainable development, our study provides empirical evidence for reducing food waste and achieving United Nations Sustainable Development Goals (UNSDG) 12.3 globally (United Nations 2015). Although we focus on FDL in this paper, our results have broader practical significance given the widespread existence of similar information asymmetries and various labels among economic societies.

The findings from this study make several contributions to the current literature. First, different from previous studies that qualitatively describe the effect of the various information on consumers' food waste behavior and intention, this study quantitatively examines the causal relationship of the FDL information on consumers' waste behavior. The results indicate that consumers' misunderstanding of FDL is an essential cause of food waste, and popular scientific information about the meaning of FDL will reduce per capita 0.34 kg of milk or cookies waste yearly by improving their cognition. Second, this study extends the existing research by showing the role of consumer labeling cognition in their food waste intentions, which also has excellent potential in transition economies and among non-perishable food. Third, this study highlights the different roles of different types of labels in reducing food waste and quantitatively identifies the potential.

The rest of the article is organized as follows: Section "Literature review" summarizes and reviews the existing literature. Section "Methods" briefly overviews the sampling strategy and intervention experiment design, definition of core variables, econometric models, samples, and data. Section "Results" presents the empirical results, robustness checks, and heterogeneity analysis. Section "Discussion" is for further discussion of the results, limitations, and implications, and the final section concludes the article.

Literature review

In the first strand of studies, the FDL has been extensively discussed in the food industry and food science fields. Due to physical or chemical changes inherent in food or due to the growth and activity of microorganisms, food gradually deteriorates during storage (Mataragas et al. 2007), which is closely related to the formulation of FDL. Accurate estimations of food spoilage and the FDL are critical, and it is not surprising that researchers from the food science and technology area have published the highest number of studies in this field (Patra et al. 2020). Although there are a lot of experiments and predictions

on the determination of food spoilage and date labeling based on the number and growth rate of microorganisms in food (Griffin et al. 2009), Weston et al. (2020) point out that the current practice of arbitrarily mark the FDL without scientific experiments and tests on bacteria aggravates food waste, and advocates the use of anthocyanin-based sensors to help consumers determine whether foods contain excessive bacteria.

Researchers in the social sciences are just beginning to explore this question, and they explore consumers' cognition of FDL and reveal a widespread misunderstanding in developed countries. For instance, Kosa et al. (2007) find that only 18% of American consumers correctly define the "use by" date label. Most of them incorrectly regard the "use by" date as a food safety indicator (Neff et al. 2019), while this definition is correct for European Union residents (Toma et al. 2020). Kavanaugh and Quinlan (2020) find that only 57.4% of consumers correctly identify what "best by, use by" means, while 68.1% and 79.7% correctly identify the definitions of "expiration date" and "sell by date," respectively. However, these studies mentioned are all based on consumers from developed countries and lack evidence from transition economies.

Further, research that aims to understand FDL's role in consumer behavior and intention is a small, emerging field (Hall-Phillips and Shah 2017). Most existing studies on the relationship among FDL cognition, food waste and intention are based on qualitative examinations, and the relevant quantitative studies are relatively few. Hall-Phillips and Shah (2017) adopt the qualitative research method and construct a conceptual model to sort out the impact mechanism of American consumers' unclarity and confusion about FDL on their cognition, perishable food purchase, and food waste behavior. Neff et al. (2019) find that 84% of American consumers discard food near the label date at least occasionally, and their research mainly uses a five-level Likert scale to measure the relative frequency of consumers' discards of different foods when they are close to or past the "use by" date. Wilson et al. (2018) use different FDL to evaluate how date labels influence the consumers' willingness to waste (WTW), and the results show that WTW is most significant in the "use by" label and is lowest for the "sell by" label. Although this study distinguishes label types, it mainly speculates on consumers' label cognition based on research assumptions and does not measure their actual cognition, and there is a lack of comparative analysis using the two-phase data. Toma et al. (2020), Thompson et al. (2018), and Thompson et al. (2020) all use structural equation models to explore the impact of using FDL on food waste. Thompson et al. (2020) focus on the effects of consumers' label-checking behavior on food waste rather than cognition. Thompson et al. (2018) quantify consumers' willingness to consume the food on and after the best before date, while they do not consider that many consumers discard food before its expiration date because of concerns about freshness. Toma et al. (2020) add consumers' sensory judgment of food for further analysis based on the two mentioned studies. The existing limited quantitative studies on FDL cognition and its effect on food waste behavior and intention come from the United States and several European countries. There is a research gap in the transition economies. Due to consumers' misunderstanding, food waste may be more severe in transition economies with relatively backward food technologies and regulations. In addition, existing qualitative studies mostly use "yes" or "no" to measure consumers' waste decisions (Connors and Schuelke 2022; Thompson et al. 2020), and it is still unclear when consumers discard food under different labels. Last,

existing studies mainly focus on perishable food, especially dairy products (Campbell and Feldpausch 2022), and lack of attention to non-perishable foods.

Numerous policies and campaigns have been developed and implemented to prevent food waste, with information campaigns representing a critical approach (Stancu and Lahteenmaki 2022; Dai and Gong 2024). Some FDL studies have used information intervention experiments to conduct exploratory research. In contrast, many questions remain unanswered due to the limited amount of research. Turvey et al. (2021) discuss the effect of popularizing the meaning of FDL to consumers by presenting interpretative statements of date labels and find that the overall understanding of “best if used by” increased from 64.0 to 82.0%, and that of “use by” increased from 44.8 to 82.4%, while they have yet to discuss further the effects on food waste intention or behavior. By informing the participants that the color, smell, and storage conditions are normal, Gong et al. (2022) find that information based on sensory factors can significantly improve their willingness to consume the food just one day past its expiration date. Although the study considers the impact of information on consumers’ food waste intention and behavior, it fails to observe the detailed date changes because consumers’ discarding date changes may be gradual and subtle. These studies all mention the importance of education and the popularization of information, providing valuable references. However, quantitative evidence for how much information intervention affects cognition and food waste intention and the potential of different labels for food waste reduction lacks evidence.

Methods

Sampling strategy

Considering that consumers may have different understandings of FDL according to different types of food (perishable and non-perishable) (Toma et al. 2020), we select two types of foods in daily life, milk (perishable) and cookies (non-perishable) products, both are long-shelf-life (generally more than three months) prepackaged foods which are widely purchased and common in daily life, as our primary research mediators to reconstruct the real daily food consumption behaviors and decisions of the interviewees as true as possible. In China, processed food includes bulk food and prepackaged food (quantified, standard products with the same characteristics placed uniformly on shelves), and only prepackaged foods have FDL. To ensure the study’s validity, we obtain data from the China Statistical Yearbook from the past five years of per capita milk consumption. By ranking the average quantity of milk consumption over five years in various regions (province, autonomous region, and municipality, simplified by “province”), we divide it into three levels (high, medium, and low) according to the numerical value. Considering the characteristics of per capita gross domestic product and regional distribution in the three categories, we select six provinces (more representative in each category) and take the corresponding capital cities as the survey sites, which are “high level”: Beijing and Xining city (Qinghai province); “medium level”: Chengdu city (Sichuan province) and Hefei city (Anhui province); “low level”: Guangzhou city (Guangdong province) and Changchun city (Jilin province), covering eastern, central and western China evenly.

We conducted an online questionnaire survey with random sampling in 2023 via a professional Chinese survey corporate “Questionnaire Star” (<https://www.wjx.cn>, a platform similar to “Synata”). The “Questionnaire Star” has over 6.2 million registered users, including over three million active users, which guarantees random sampling and covers 31 provincial administrative divisions in China (excluding Hong Kong, Macao, and Taiwan). The survey company consistently provides qualified survey distribution and collection services through screening participants with an integrity score system. “Questionnaire Star” can be assessed through a smartphone, which is widely available in China and thus covers the participants with diversified characteristics (Lin and Guan 2021). The questionnaire survey focuses on the essential statistical characteristics of participants, participants’ cognition of FDL, food waste behavior and intention, and the information intervention, which can be found in the supplementary material (S1). Before administering the survey, we consult three professors who are very senior in the field of data survey and food consumption and modify the questionnaire according to their feedback. After that, we conduct an offline questionnaire survey on 34 voluntary participants in the form of face-to-face discussion to understand the problems that might cause comprehension difficulties in their answering process and ask for improvement advice after the survey. Further, we conduct 308 pre-surveys online before launching the formal survey to determine whether its items are clear and straightforward to understand in a random sample based on the selected survey site. We ensure the content validity through such elaborate operations in the early stage.

Participants should be at least 18 years old and are allowed to submit once. The intervention and control groups are independent and randomized, with no duplicate samples. In addition, the distribution of samples based on milk or cookies is random, and the same participant will not answer the questionnaire for both food types or the intervention and control groups. In other words, participants are unaware of whether they are in the intervention group or not and are unable to choose which food types they are involved in. Participants in the pre-survey are not invited to participate in the formal survey, and participants in the formal survey do not receive any information or training prior to the survey. Since the survey company has an independent code for each participant, the random and non-repetitive questionnaire delivery requirement is well controlled. We also exclude samples that take too short or too long to ensure the validity of the intervention. After cleaning data, we collect 8,882 valid samples from six cities. Furthermore, to avoid the impact of the selected food types on the survey results, we also exclude 306 participants who do not consume milk or cookies (with 712 samples), which means there will be no waste of either kind of food, to yield a final sample valid size of 7,830 (see Fig. S1 for regional and sample distribution).

Experiment design

With reference to research on food waste based on stimulus-organism-response theory (Talwar et al. 2022), we design our experiment accordingly and the whole process of the experiment is shown in Fig. 1. Participants enter our questionnaire interface through mobile phones or computers. In addition to the setting of the intervention content, the questions answered by the intervention and control groups are exactly the same. First, we acquire consumers’ cognition of three widespread food date labels in the Chinese

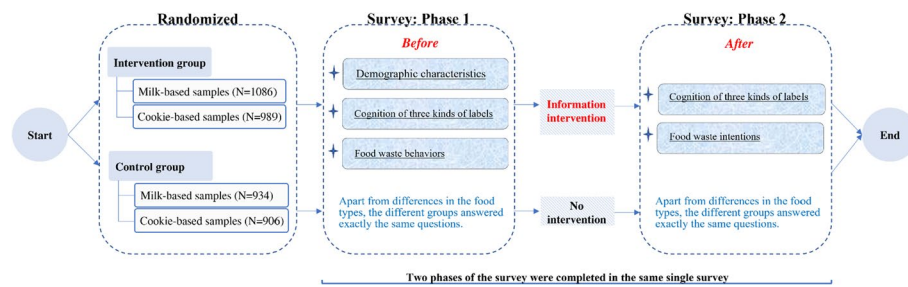


Fig. 1 Experimental procedure

Table 1 The content of the information intervention experiment

Label types	Meanings
Best before date label	A quality indicator indicates food's optimal taste and flavor, which will decline beyond this date but is edible
Quality guaranteed date label	A quality indicator indicates food's optimal taste and flavor, which shares the same meaning as the best before date
Use-by date label	A safety indicator indicates the last edible date. Food beyond this date is no longer recommended for consumption and poses a health risk

market. They are “quality guaranteed date label,” “best before date label,” and “use-by date label,” and the pictures used in the formal survey process (in Chinese form) are shown in S1, which is the questionnaire in English and milk version. We also acquire the amount of expired milk or cookies they wasted, the date they discarded the food before or after the date indicated on the corresponding food date labels, and a series of personal information questions in the questionnaire. Second, we immediately display the intervention content on the screen (as the role of stimulus). For the intervention group, the contents are shown in Table 1 for details. The screen displays the following content for the control group: “This page is intentionally left blank”(in Chinese). After receiving the information stimulus, we expect that the information stimulus will have an impact on the participants, and participants will respond accordingly. Subsequently, we measure the participants’ new cognition of three date labels and food waste intentions regarding the amount and date of food discarded to collect data for the second phase to determine the effectiveness of the intervention. The specific changes are shown in Table 2. It should be noted here that the whole process described above occurs in a short period of time—immediately after the information intervention, we require the participants to report the new cognition and the expected intention, which avoids the possible “side effects” of the intervention (Cicatiello and Franco 2020) to obtain the real effect of the intervention.

Last but not least, considering different expressions of food date labeling share the same meaning of “best before date” in China, which differs from the meaning of international food date labeling, our definition of Use-by date label in the experiment is inconsistent with the regulations in reality. Taking into account the potential for misleading caused by our intervention, we use an explanatory page at the end of the questionnaire to explain the specific meanings of the date labels in China to prevent further misunderstanding from our intervention experiment and try to play a role in popularization, which writes “The quality guaranteed date label in China generally refers to the period

Table 2 Descriptive statistical analysis of key variables

Dependent variables	Cognition (%)			Behavior (date)		
	Before	After	Diff	Before	After	Diff
<i>The intervention group</i>						
Quality guaranteed date label	20.39%	64.77%	***	− 0.16	1.33	***
Best before date label	76.19%	93.45%	***	1.19	2.24	***
Use-by date label	20.77%	87.04%	***	− 0.49	− 0.86	***
Three answers are correct	5.93%	59.42%				
Two answers are correct	22.80%	27.23%				
One answer is correct	53.98%	12.53%				
Zero answer is correct	17.30%	0.82%				
Mean (scores)	1.17	2.45				
Food (milk or cookies) waste (kg/per capita/month)				0.10	0.06	***
Number of observations	2075	2075		2075	2075	
<i>The control group</i>						
Quality guaranteed date label	17.55%	15.43%	*	− 0.08	− 0.07	
Best before date label	74.46%	79.13%	***	0.96	1.00	
Use-by date label	25.05%	74.67%	***	− 0.28	0.30	
Three answers are correct	7.07%	6.47%				
Two answers are correct	21.30%	59.08%				
One answer is correct	53.26%	31.68%				
Zero answer is correct	18.37%	2.77%				
Mean (scores)	1.17	1.69				
Food (milk or cookies) waste (kg/per capita/month)				0.12	0.11	
Number of observations	1840	1840		1840	1840	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The significance here represents the paired samples t-test results (H_a : diff = 0) of the corresponding cognition and behavior variables changes before and after the intervention to verify if there are any significant changes

from the production to the apparent change in the flavor of prepackaged food under the storage conditions specified on the label, which is the period of quality maintenance, rather than the standard of food deterioration and inedibility.”

The definition of the food waste behavior and intention

We draw on the definition of food waste from the FAO (2011), which refers to the food discarded that is still edible (excluding inedible parts). Considering the meaning of the FDL in China is the same as the “best before date label,” food discarding date near the date indicated on the label is regarded as food waste behavior in this study. In the questionnaire, we require participants to report the amount of expired milk or cookies they throw away monthly. Given that the FDL of milk and cookie products is mostly 3–6 months or more, it is difficult to capture this waste in a shorter period, such as in the past three days or a week. Considering this kind of food waste may not happen every month (may happening once every few months), we ask participants to recall their average monthly discards over the past year to obtain these data. Since it is difficult for participants to recall further the types of labels associated with discarded milk or cookies, we measure this waste by asking about the date food is discarded under the three types of labels separately. More precisely, in the questionnaire, we require participants

to report the last date they stop consuming and to discard the food under different food date labels—one date before or after the expiration date (five days to the expiration date, four days to the expiration date (in descending order, named numbers “-5”-“-1”), the expiration date (named number “0”), one day after the expiration date (in ascending order), nine days after the expiration date and ten days after the expiration date (named numbers “1”- “10”), a total span of 16 days). After the information intervention, we require participants to report an expected reduction in the proportion of milk or cookies and their future food waste dates under different labels again to obtain their food waste intentions. Specifically, the increase in the average waste date indicates that the duration of the food prolongs, which means that consumers are more tolerant of the food near the date stated on the labels and are more likely to finish them instead of wasting, regarded as less food waste.

Descriptive statistical analysis of core variables

The information transmission function of food date labeling is seriously damaged due to the widespread misunderstanding of different labels. 84.46% of participants report they are used to using FDL during the purchase process, while the simultaneous cognitive accuracy of the three labels is only 6.46%, according to China’s FDL definition. Consumers have the highest cognitive accuracy (75.38%) for the “best before date label.” It is worth noting that the “quality guaranteed date label,” the most commonly used in China, has the lowest rate, only 19.05% among consumers. Our judgment of the “use-by date label” here is based on China’s definition of quality indicator, which differs from the information intervention content. After the information intervention, the cognitive accuracies of both “quality guaranteed date label” and “best before date label” significantly improve to 64.77% and 93.45% in the intervention group, respectively. Since the “use-by date label” intervention content is the same as consumers’ common wrong cognition before information intervention, the significant cognition change of consumers in the control group for label “use-by date label” after the information intervention is largely due to the different definition of label “Use-by date label” before and after the experiment, and the effect of this difference in definition will be eliminated in subsequent measurement models. In addition, the reasons for the significant changes in food date labeling cognition of consumers in the control group after the information intervention will be detailed in the third paragraph of “Further exploration of the results.” For food waste behavior, it is common for consumers to waste food before (date < 0) the dates shown on the “quality guaranteed date label” and “use-by date label” before the information intervention. After the information intervention, the expected amount of food waste intention and the specific waste date in the intervention group change significantly, while there is no significant change in the control group.

Descriptive statistical analysis of control variables

Table 3 shows the description of the demographic variables of all samples. We obtain samples from the selected six cities, which covers eastern, central, and western regions of urban China well. Males account for 43.96% of the participants. The average age of

Table 3 Sample descriptive statistical analysis

Control variables	Description	Mean	SD
<i>Demographic variables</i>			
Age	Years old	29.98	7.19
Gender (n/%)	Female	2194 (56.04%)	
	Male	1721 (43.96%)	
Education qualification (n/%)	Below bachelor degree	805 (20.56%)	
	Bachelor degree	2677 (68.38%)	
	Above bachelor degree	433 (11.06%)	
Occupation (n/%)	Clerical staff	693 (17.70%)	
	Managerial personnel	471 (12.03%)	
	Current student	453 (11.57%)	
	Professional technical personnel	453 (11.57%)	
	Administrative and support staff	348 (8.89%)	
	Technology research and development personnel	267 (6.82%)	
	Service staff	243 (6.21%)	
	Teacher	186 (4.75%)	
	Employees in the food industry	164 (4.19%)	
	Freelancer	158 (4.04%)	
	Individual businessman	133 (3.40%)	
	Retiree	22 (0.56%)	
Risk attitude	Risk aversion = -1	2682 (68.51%)	
	Risk neutral = 0	248 (6.33%)	
	Risk preference = 1	985 (25.16%)	
<i>Household variables</i>			
Household population	The number of living family members	2.95	1.30
	number < 3	1370 (34.99%)	
	number = 3	1397 (35.68%)	
	number > 3	1148 (29.32%)	
Number of elderly people	The number of elderly living family members (over 65 years old)	0.26	0.61
Number of children	The number of children living with family members (below 18 years old)	0.61	0.67
Health state	Whether all living family members are healthy (including the participant)? (No = 0; Yes = 1)	0.77	0.42
Per capita disposable income	Yuan (CNY, Chinese currency unit) per month		
	< = 2500	1352 (34.53%)	
	(2500–5000]	1341 (34.25%)	
	> 5000	1222 (31.21%)	
<i>Food waste attitude variables</i>			
Frugal	I am very frugal with food. (7-point Likert scale: Strongly disagree = 1; Neutral = 4; Strongly agree = 7)	5.37	1.21
Morality	I feel very guilty inside when I throw away food. (7-point Likert scale: Strongly disagree = 1; Neutral = 4; Strongly agree = 7)	5.38	1.25
<i>Food consumption habits variables</i>			
Planned	I always have a plan when purchasing food. (7-point Likert scale: Strongly disagree = 1; Neutral = 4; Strongly agree = 7)	5.63	1.06
Freshness requirement	The freshness requirements for food when purchasing. (0–4 continuous integer variable, no requirement = 0; the highest requirement = 4)	1.98	1.01
Purchasing frequency	1–11 continuous integer variables increase frequency as the number increases	9.01	1.96

Table 3 (continued)

Control variables	Description	Mean	SD
<i>Label attitudes variables</i>			
Perception of FDL usefulness	FDL is meaningful. (7-point Likert scale: Strongly disagree = 1; Neutral = 4; Strongly agree = 7)	6.10	0.97
Dependence on the FDL	I judge whether the food is still edible by myself, not relying on the FDL. (7-point Likert scale: Strongly disagree = 1; Neutral = 4; Strongly agree = 7)	2.36	1.33
<i>Food types</i>			
	Milk-based samples	2020 (51.60%)	
	Cookie-based samples	1895 (48.40%)	
<i>Region variable</i>			
Eastern China	Including Beijing city and Guangzhou city	1355 (34.61%)	
Central China	Including Hefei City and Changchun City	1286 (32.85%)	
Western China	Including Chengdu City and Xining City	1274 (32.54%)	
Number of participants		3915	

One CNY was equal to 0.1408 US dollars in March 2023. "FDL" is the acronyms of "food date labeling". According to the criteria set by the National Bureau of Statistics of China, the eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes eight provinces: Heilongjiang, Jilin, Henan, Shanxi, Anhui, Jiangxi, Hubei, and Hunan, and the remaining provinces are classified as the western region

participants is 29.98, which is consistent with the basic situation of Chinese netizens,² and women show more concern about food issues (Jiang et al. 2023). Regarding education and work, 68.38% of the participants have received their bachelor's degree diplomas. Although this level of education is higher than the current level of education of Chinese netizens, it is reasonable given the particularity of online survey methods. We verify that the education level of the participants in our survey is representative by comparing the China-based studies (Chen et al. 2024; Jiang et al. 2023) that also use the online survey method and this phenomenon is universal (Talwar et al. 2022). The per capita monthly disposable income is about 4835 yuan, representing the income of urban residents and netizens^{3,4}. In summary, the data samples tend toward more females, younger, and more educated people and have good coverage and representation among urban residents and netizens in China.

Econometric models

We first explore the relationship between FDL cognition and food waste behavior. Considering that this part is actual consumer behavior based on the first phase cross-section data before the information intervention, we use ordinary least squares (OLS) regression to conduct empirical analysis, and the specific formula is as follows:

$$Cognition_i = \beta_0 + \beta_1 FW_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

where $Cognition_i$ is individual FDL cognition, which includes both the overall cognition and the cognition corresponding to different labels; i denotes the participant individual;

² <https://www.cnnic.net.cn/NMediaFile/2024/0325/MAIN1711355296414FIQ9XKZV63.pdf>

³ https://www.cac.gov.cn/2021-02/03/c_1613923423079314.htm

⁴ http://big5.www.gov.cn/gate/big5/www.gov.cn/lianbo/bumen/202404/content_6945489.htm

FW_i is the amount of food wasted due to expired milk or cookie of each participant and their date of food waste before the intervention experiment corresponding to different labels; X_i stands for control variables, including participant's demographic variables, family variables, food date label attitudes, food waste attitudes, food consumption habits, food types, and region dummy variables, consistent with the variables in Table 3, and ε_i is the error term.

Second, a paired samples t-test, a within-subject analysis method is performed to check whether significant changes could be observed between the two phases of panel data—participants' labeling cognition and behavior before the information intervention and their cognition and intention after the intervention. Regarding cognition, we distinguish between the intervention and control groups and investigate the analysis of the overall label cognition and the individual label cognition change. A line of thought consistent with cognition analysis is used regarding behavior. The significant results are shown in Table 2, which provides a basis for further quantitative analysis.

Third, we use the difference-in-differences (DID) model, an analysis method combines within-subject and between-subject to evaluate the net effect of the information intervention on consumers' FDL cognition and food waste intention. DID is the most prevalent and the oldest quasi-experimental research method. And among the methods to evaluate the effect of policy implementation, the DID model is an econometric method widely used in recent years (Feng et al. 2021; Wang and Ge 2022). The basic idea of this method is to regard the implementation of a new policy or intervention as a "natural experiment" or "quasi-experiment" that is exogenous to the economic system (Chen and Wu 2015). On the one hand, implementing our information intervention may make the participants' label cognition, food waste behavior and intention different before and after the intervention. On the other hand, the above two indicators may differ between the intervention and control groups at the same time. The DID model regression estimation can effectively control the impact of other synchronous interventions and the prior difference between the intervention and control groups to identify the net effect of the intervention (Wang and Ge 2022). See the following formula for model construction:

$$Cognition_{it} = \alpha_0 + \alpha_1 treat_i \times post_t + \alpha_2 X_i + \lambda_i + v_t + \varepsilon_{it} \quad (2)$$

$$FW_{it} = \delta_0 + \delta_1 treat_i \times post_t + \delta_2 X_i + \lambda_i + v_t + \varepsilon_{it} \quad (3)$$

where $Cognition_{it}$ represents the participant's FDL cognition before and after the information intervention; FW_{it} represents the participant's food waste behavior before the information intervention and the food wastes intention after the information intervention; the index $t = 0$ and 1 identifies a time series of data; $treat_i$ is a dummy variable representing the group effect of the intervention group, and this dummy variable is extracted from the survey; $post_t$ denotes a time dummy variable, which captures the time effect of the intervention period. $treat_i \times post_t$ represents the real effect of the intervention group during the intervention period. Our key interest is in the coefficients α_2 and δ_3 , which represent the net effect of the intervention on label cognition and food waste intention, respectively. λ_i represents the individual fixed effect and v_t represents the time fixed effect.

Results

The relationship between the food date labeling cognition and the food waste behavior

Benchmark regression results

We use cross-section data from the first period of panel data and OLS regression to explore the relationship between consumers' FDL cognition and actual food waste behavior. The results shown in Table 4 indicate that consumers' cognition of FDL significantly affects their food waste behavior, which contributes an essential supplement to the quantitative research of this relationship (Hall-Phillips and Shah 2017). We first analyze the overall cognition level of the three labels and the reported weight of discarded milk or cookie due to expiration, and then further refine the study by examining the waste dates under different labels, which make up for the current lack of evidence on consumers' food waste under according labels.

The regression results show that each FDL meaning that consumers answer correctly is associated with less per capita 0.010 kg of milk or cookie waste per month (see (1) column of Table 4 in details). Regarding specific labels, the relationships between the three labels and the corresponding food discard date pass the significance level of 1%, which significantly confirms the positive relationship between consumers' FDL cognition and their corresponding food waste behaviors. Further, consumers who correctly answer the meaning of the quality guaranteed date label, the best before date label, and the use-by date label keep their food for an average of 1.095 days, 2.040 days, and 0.693 days longer than those who misunderstand these labels (see (2–4) columns of Table 4 in details), which means that different labels have different impacts on consumers' food waste behavior. The effect is most significant for the best before date.

Table 4 Benchmark regression results of the relationship between cognition and waste behavior

Variables	(1) <i>FW_{amount}</i>	(2) <i>Date₁</i>	(3) <i>Date₂</i>	(4) <i>Date₃</i>
<i>Cognition_{All}</i>	− 0.010** (0.004)			
<i>Cognition_{Quality_guaranteed}</i>		1.095*** (0.144)		
<i>Cognition_{Best_before}</i>			2.040*** (0.127)	
<i>Cognition_{Use-by}</i>				0.693*** (0.114)
<i>Control variables</i>	Yes	Yes	Yes	Yes
Constant	0.172*** (0.041)	− 1.060 (0.680)	− 1.602* (0.860)	− 0.534 (0.607)
<i>R-squared</i>	0.043	0.086	0.092	0.060
Observations	3,915	3,915	3,915	3,915

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *FW_{amount}* is short for the "Per capita amount of food (milk or cookie) waste monthly." *Date₁*, *Date₂*, and *Date₃* represent the food waste date under the quality guaranteed date label, the best before date label, and the use-by date label

Robustness test

We use two methods to test the robustness of the results. (1) *Changing sample*. Considering that different consumers have different food consumption habits and preferences, to exclude the influence of our food type choice on the results, we retain the samples that do not consume milk or cookies and conduct regression based on the total sample of 4221. The regression results are shown in Table S2, which confirm the excellent robustness in a broader sample group in all four regressions. (2) *PSM*. Propensity score matching (PSM) is a suitable method for reducing bias and controlling the effect of observable variables, thereby producing a quasi-random trial effect (Zhang et al. 2022). Here, we adjust the original overall cognition level of the three labels to the dummy variable, indicating whether they have a correct understanding of any of the labels (naming equal to “0” as “0” and naming greater than “0” as “1”), and use the PSM method to perform kernel matching between the two groups to verify the randomness. Since the specific labels are already 0–1 dummy variables, we directly group matching according to the corresponding cognitive state. The common support domains are shown in Fig. S2(a, c, e, g), and the matching observable variables included are shown in Fig. S2(b, d, f, h); the bias of each variable is closer to zero, indicating that our match is effective and that we can conduct further robustness tests (Deng et al. 2024). Based on the matched samples, we conduct further regressions, and the results are in Table S3, which also verifies the robustness.

Heterogeneity analysis

We further explore the heterogeneity of the results. In the regression analysis of the three regions, we find that although the regulation and definition of FDL is consistent across the country, its impact on food waste only shows significance in the eastern region. In comparison, for the other two regions, the relationship fails to pass the significance test (see Table S4 for details). This means that taking the eastern region as a critical area to popularize the meaning of FDL may be an effective and targeted measure to reduce food waste. In addition, since cognition is often thought to be related to education level (Ritchie and Tucker-Drob 2018), we conduct group regression for participants with different education levels to further explore. As shown in columns (4–5) of Table S4, the relationship between FDL cognition and food waste passes the significance test in both education levels, which means that higher education does not mean less food waste due to misunderstanding. On the contrary, it is a common problem that requires extensive publicity and education across the whole society.

Further, we are interested in the differentiated effects of labels on two types of food. As shown in Table S5, each regression passes the significance test, meaning that participants' cognition of different labels significantly impacts food waste in both food types. This means that not only is perishable food crucial to food waste (Connors and Schuelke 2022; Thompson et al. 2018), but non-perishables' impact on food waste is equally important while underestimated.

The net effects of the information intervention

The intervention net effect on cognition

The information intervention significantly improves consumers' cognition of FDL, especially the quality guaranteed date label. Although we have presented statistical analysis

Table 5 Benchmark regression results of the intervention effect on cognition

Variables	(1) <i>Cognition_All</i>	(2) <i>Cognition_Quality_ guaranteed</i>	(3) <i>Cognition_Best_before</i>	(4) <i>Cognition_Use-by</i>
<i>did</i>	0.757*** (0.033)	0.465*** (0.018)	0.126*** (0.017)	0.166*** (0.018)
<i>Control variables</i>	Yes	Yes	Yes	Yes
Constant	0.673*** (0.122)	− 0.066 (0.067)	0.590*** (0.065)	0.149** (0.066)
Individual fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
<i>R-squared</i>	0.360	0.220	0.065	0.353
Observations	7830	7830	7830	7830

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Due to the different definitions of “Use-by date” label before and after the experiment, the DID model can better identify the net effect of intervention

Table 6 Benchmark regression results of the intervention effect on food waste intention

Variables	(1) <i>FW_{amount}</i>	(2) <i>Date₁</i>	(3) <i>Date₂</i>	(4) <i>Date₃</i>
<i>did</i>	− 0.028*** (0.008)	1.483*** (0.141)	1.013*** (0.177)	− 0.351*** (0.114)
<i>Control variables</i>	Yes	Yes	Yes	Yes
Constant	0.181*** (0.029)	− 1.737*** (0.528)	− 1.080* (0.641)	− 0.124 (0.416)
Individual fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
<i>R-squared</i>	0.050	0.091	0.058	0.049
Observations	7830	7830	7830	7830

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *FW_{amount}* is short for the “Per capita amount of food (milk or cookie) waste.” *Date₁*, *Date₂*, and *Date₃* represent the food waste date under the quality guaranteed date label, the best before date label, and the use-by date label, respectively

in Table 2, we use two-period panel data (before and after the intervention) and the DID model to empirically analyze the net effect of the intervention. The results indicate strong evidence that information significantly improves participants’ overall cognition and all three labels’ cognition, and the net cognition changes resulting from the intervention are shown in Table 5. The coefficients indicate that the net effect of an information intervention on the quality guaranteed date label is the largest, which means that the intervention improves this label’s correct cognition net value by 0.465 average. Compared with the original highly correct cognition of the best before date label, the scientific popularization of the meaning of quality guaranteed date labels will be more efficient.

The intervention net effects on food waste intention

The information intervention significantly helps to change food waste intention, and the quality guaranteed date label has the most significant potential for reducing food waste. The information intervention substantially reduces the net amount (0.028 kg)

of food that participants are expected to discard and significantly changes consumers' food waste intention under different labels. The most significant change comes from the intervention of the quality guaranteed date label, with an average prolonging of 1.483 days (see Table 6 for details). The best before date label, with the same meaning as the quality guaranteed date label, has an average prolonging of 1.013 days. In addition, information intervention has a significant adverse effect on consumers' waste intention of the use-by date label, which is in line with our expectations and means the waste date of this label (as a safety indicator) is generally advanced by 0.351 days to prevent the foodborne diseases caused by food spoilage. Although some scholars have verified the influence of information on food waste (Dai and Gong 2024), our study conducts a complementary study from the perspective of the meaning of FDL, which further confirms the critical role of information in reducing food waste and fills the research gap.

Robustness test

We use three methods to verify the robustness of the results for both the change of cognition and intention. (1) *PSM-DID*. Combining PSM with DID to achieve a quasi-random trial effect has been widely used in the impact assessments of policies (Fu et al. 2021; Deng et al. 2024). Therefore, although our study is a typical randomized trial, we use kernel matching to match the sample for additional regressions to avoid the influence of potential bias on the results in the actual operation. Figure S3(a) shows the common support domain, and the matching observable variables are included in Fig. S3(b). The bias of each variable is closer to zero, indicating that our match is effective. Based on the matched samples, we conduct further regressions for both cognition and intention, and the regression results are shown in Tables S6 and S7, respectively. All coefficient estimates pass the significance test at the level of 1%, which is consistent with those of the benchmark DID regressions and further indicates that the results are robust. (2) *Placebo test*. We further conduct placebo tests to avoid the influence of possible interference of random factors and perform the random sampling 1000 times for cognition and intention. Figure S4 displays the kernel density distributions of the estimated coefficients for random samples, and equations are concentrated on both sides of "0" and follow a normal distribution, indicating that random factors do not affect the cognition and intention and further validating the robustness of the results (Deng et al. 2024). (3) *Kruskal–Wallis test*. A one-way analysis of variance by ranks (nonparametric test) to confirm further the net effect of information intervention on overall labeling cognition and intention change to ensure the robustness of the effective role of information intervention. Compared with the parameter test, the nonparametric test does not make any requirements on the distribution type of the data, is not affected by the overall parameters, and has a wide range of application, which can be used for statistical analysis of any data with better statistical efficiency. First, we use the Kruskal–Wallis test to examine the effect of information intervention on overall cognition and intention changes between the intervention and control groups. The results are $\chi^2(1) = 559.231$, $p = 0.0001$, $\chi^2(1) = 275.138$, $p = 0.0001$, respectively, which pass the test at the significance level of 1% and verify the effectiveness of the information intervention between the groups. Second, we validate the effect of the intervention on cognition and intention across different label types in the intervention group. The results are Chi-squared (corrected for

ties) = 911.064 ($p = 0.00010$), Chi-squared (corrected for ties) = 500.570 ($p = 0.00010$), respectively. Both pass the test at a significance level of 1% and verify the effectiveness of the information intervention between the groups. Through further pairwise comparison, we find the differences between the pairwise are all at the significance level of 1%, showing that the three labels show significant differences in cognition and intention changes, which support and echo the findings.

Heterogeneity analysis

We move on to heterogeneity analysis to further explore the potential differentiated impact of information intervention. By differentiating regions and levels of education, we conduct separate regressions for the overall FDL cognition change, and the results are shown in Table S8. The results show that information intervention significantly and positively affects participants' FDL cognition in all groups, effectively proving the information intervention's effectiveness and universal applicability.

In addition, for different types of labels, we explore the effects of information intervention between two types of foods on their corresponding food waste intentions, and the results are shown in Table S9 for details. In contrast to existing research focusing on perishables, the results here support the potentially important role of non-perishables in reducing food waste, which has been very insufficient in previous studies. In addition, for both types of food, quality guaranteed date label is the label with the greatest potential to reduce food waste. This inspires us that it is very necessary and urgent to convey the correct meaning of quality guaranteed date label to the public no matter for perishables or non-perishables.

Discussion

Further exploration of the results

We focus on the quality guaranteed date label, the best before date label, and the use-by date label, which share the same meaning (quality indicator) and are supposed to play the same role in China, and explore the differences among these labels from the consumer perspective. Compared to the most widely used quality guaranteed date label, the best before date label enables consumers to understand the correct meaning better. Even though the quality guaranteed date label contains the "quality" word directly, it is still widely seen as an indicator of food safety, which is similar to the finding of Neff et al. (2019) that consumers mistakenly regard food quality indicators as safety indicators. The quality guaranteed date label needs to be focused on because it is the most confusing and widely used label, and it has the highest net effect on consumers' label cognition and intention change after the information intervention.

Further, compared to Gong et al. (2022) study on whether consumers will continue to eat yogurt one day after its expiration after being informed of food status information, our study uses the change of successive dates to measure the influence of information on food waste intention. Although it should be admitted that the shift in food waste date brought by the change of label cognition may not be linear, such a subtle and further study is still necessary because the change of cognition is a gradual process, and this setting can better capture slight changes in food waste intention to predict actual behavior.

In particular, we find some interesting results from the statistical analysis results in Table 2 and do some further digging here. Although the control group does not receive the information intervention, we find that participants in this group also experienced significant changes in FDL cognition, which is beyond our expectations. These results show that our experiment also makes our participants in the control group to re-examine and re-think the meaning of different labels. However, although participants' effort shows an overall cognition improvement, this effort hurts the quality guaranteed date label, which seems to indicate that the quality guaranteed date label is misleading in a literal sense. This shows us the importance of allowing consumers to understand the label literally, leading us to a parallel path to propagate the meaning of FDL.

Finally, as for the use-by date label, regarded as a food safety indicator in many countries (Busetti 2019), we do not follow the Chinese definition of this label but set its meaning as a safety indicator in the information intervention process. Fortunately, this deliberate and different definition significantly negatively impacts consumers' food waste intention in the (4) column of Table 6. This result confirms the effectiveness of our information intervention (participants show different responses to different labels) and sheds new light on subsequent measures to differentiate the meaning of labels in China, which provides a forward-looking exploration.

Limitations

In the discussion of the results of this study, its limitations should be kept in mind. First, like most research in this field, we use recalling and self-reporting methods to assess the amount of food waste. However, it has been pointed out that the weaknesses of self-report measures of food waste may be accompanied by measurement errors (results lower than the actual value) (Talwar et al. 2022). Considering the human resources, financial resources, and difficulty of carrying out offline field surveys, we chose the online survey with a larger sample size to make up for the accuracy of the offline survey, which is a kind of trade-off. Further ongoing follow-up investigation in the future can further deepen our research and obtain the actual waste behavior change after the information intervention rather than the intention. Second, considering the Internet penetration rate in rural areas is 66.5%, and rural Internet users only account for 29.8%⁴ of the total Internet users in China, it is difficult for the online questionnaire survey method to have a good representation in rural areas, so we focus on urban areas with higher Internet popularity and more concentrated users. In the future, research based on samples from rural areas is another direction. Given the differences between urban and rural food waste in China (Cheng et al. 2022), there might be different findings. Third, due to the online survey method we choose (interactive mode of text understanding and response), the samples inevitably show that the overall education level is higher than the average. Although the comparisons with other studies in food consumption confirm our samples' representativeness, it should be admitted that further investigation through offline random sampling, with a more representative distribution of educational level may be a direction of further research.

Theoretical implications

This study contributes three critical theoretical implications. First, in the context of the rapid increase of global food waste, this study responds to the call of scholars for further quantitative research in this field (Hall-Phillips and Shah 2017; Stancu and Lähteenmäki 2022), addresses the deficiencies in empirical research and contributes new insights to the existing research. Specifically, considering the critical role of household food waste in reducing food waste (Talwar et al. 2022), our study provides empirical evidence for reducing household food waste, which complements the methodology and insights for further reducing household food waste on a global scale. Second, in the context of the widespread occurrence of information asymmetry in the consumption market, our study empirically tests the relationship between consumer FDL cognition and food waste from the consumer perspective, which provides a theoretical basis for eliminating this information asymmetry. In addition, we explore the potential of different labels, which is critical to reducing food waste at the consumer end, while they have not received much attention in this context. Third, considering the essential role of suboptimal food in reducing food waste has been proven (Young et al. 2024), our research object—the food nearing its expiration date, also belongs to the category of suboptimal food research. The food waste caused by food nearing the expiration date is one of the essential contents of suboptimal food research, and our study enriches the current research on suboptimal food, which will provide new solutions to the problem of food stigma and provide empirical evidence for the maximum utilization of resources theoretically.

Practical implications

Our findings offer two practical implications that may benefit multiple stakeholders, including policymakers, non-governmental organizations, and the public. First, optimizing the labeling system will bring great potential to save food and achieve UNSDG12.3 globally rapidly. China's FDL mimics international conventions but fails to define the differences among labels. Different expressions of FDL all share the same meaning, intensifying consumers' misunderstanding and food waste, which is a lesson that policymakers in transition economies need to learn from. Due to the highly interdisciplinary nature of the research in this field, researchers need to conduct targeted scientific experiments based on the actual development ability of food science in their home countries and distinguish the meanings of different labels to reduce misunderstandings. Our information intervention experiment not only simulates the real situation of scientific popularization of the meaning of FDL, but also provides an effective prediction for subsequent science popularization, and offers ideas and feasible evidence for subsequent FDL label reform through differentiated definition of label meanings. Second, the scientific popularization of the meaning of date labels to the public is an effective way to reduce food waste, especially the quality guaranteed date labels. In addition to improving consumers' label cognition as soon as possible, directly marking the meaning of date labels on food packaging is a low-cost and effective way of information transmission and reduces consumers' confusion and misunderstanding. Further, the names of different labels should be more convenient for consumers to understand literally to reduce potential misunderstanding. Considering that the FDL cognition of consumers in eastern China is more significantly

related to their food waste behavior, it is a targeted and efficient measure to carry out scientific popularization of the meaning of FDL in the eastern preferential to accelerate the reduction of food waste.

Conclusions

It is habitual for most consumers to check the food date labels when purchasing food. However, the information transmission function of the FDL is seriously damaged. To address the research gaps and the practical issue, our study is the first worldwide to empirically verify the causal relationship among consumers' label cognition and food waste behavior and intention through econometric methods, and quantify the resulting milk or cookies waste. The results point out that increasing the popularization of FDL is a practical, simple, and potential way to reduce food waste. Considering that different information interventions have different effects on labels, we need to identify the labels that have the most significant potential impact on consumers' food waste intention and prioritize the scientific popularization of these labels to curb food waste as soon as possible. Further, information interventions should be based on localized strategies and universal outreach among different populations without ignoring the potential of non-perishable foods to reduce food waste.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s40100-025-00360-y>.

Additional file 1

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Author contributions

Shujun Cheng contributed to the formal analysis, methodology, data curation, writing-original draft, writing-review and editing. Yang Lu was involved in the methodology, software, writing-original draft, writing-review and editing. Yanjun Ren assisted in the conceptualization, formal analysis, writing-review and editing. Zhide Jiang contributed to the conceptualization, writing-review and editing. Minjuan Zhao was involved in writing-review and editing, supervision, funding acquisition and project administration.

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Availability of data and materials

Data will be made available on request.

Declarations

Ethics approval

Approval was obtained from the ethics committee of Northwest A&F University. The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent to participate

No identifying personal information was gathered about the participants, given the data were received anonymously from the research company organizing the consumer panels. Informed consent was obtained from all individual participants included in the study. Only adult respondents were included.

Competing 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.

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