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Exploring Food Values and Consumer Preferences for Mung Beans in Urban China: A Best-Worst Scaling Approach

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Abstract

This study examined the preferences of urban Chinese consumers for mung beans through a survey conducted in three major cities. Using the concept of food values and the best-worst scaling (BWS) approach, the findings highlight safety, nutrition, naturalness, and taste as key drivers of mung bean purchases. Latent class (LC) analysis further identified three distinct consumer segments: Class 1 placed the strongest emphasis on environment, followed by safety and nutrition; Class 2 prioritized safety, regardless of price; and Class 3 required both healthfulness (reflected in safety and nutrition) and good taste for a product to be selected.

Discipline: Social Science
Additional key words: latent class analysis, China's edible bean market

Introduction

Mung beans, called *lǜdòu* (緑豆) in Chinese, are a widely consumed variety of edible beans across China. According to China Grain Industry Association (2010), approximately 70% of mung bean consumption occurs in households. In Chinese homes, mung beans are commonly prepared in various ways, including cooking them with rice as a staple food and boiling them with water and sugar to create a popular summer drink. This study aims to uncover the demand characteristics of China's mung bean market by analyzing urban consumers' preferences.

China has long been one of the world's largest producers and exporters of mung beans. However, in recent years, China's mung bean market has undergone a significant transformation. In 2018, imports tripled those of the previous year, reaching 88,987 tons, and China has become a net importer of mung beans since 2020. By 2023, imports reached 572,680 tons, making China the world's second-largest importer of mung beans, while domestic production and exports declined to 350,000 and 74,573 tons, respectively (UN Comtrade; National Bureau of Statistics of China). This transformation has been driven mainly by rising domestic consumption (Zhang 2024), yet the underlying factors shaping consumer demand for mung beans remain underexplored.

The supply and demand of edible beans, other than soybeans, have received little attention in existing studies. Among the limited academic contributions, Guo (2014) explored the long-term development of the edible bean industry and concluded that total demand and the export quantity of edible beans in China would continue to increase until 2025. Conversely, Tajima & Zhang (2013) argued that the price competitiveness of Chinese adzuki and mung beans was decreasing. Zhang (2024) further claimed that the macro-structure of China's mung bean market after 2014 could be summarized as stagnating production, rising imports and decreasing price competitiveness.

Previous studies have offered little insight into the demand side of China's mung bean market, primarily because reliable price and consumption statistics are unavailable. This lack of academic accumulation, especially regarding consumer preferences, has left Chinese producers and food manufacturers without the necessary information to adapt to the changing market structure. This study addresses that gap by analyzing urban consumers' preferences for mung beans using the concept of food values and the best-worst scaling (BWS) approach. The originality of this study lies in its ability to capture the multi-attribute preferences of mung bean

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purchases, distinguishing it from conventional demand analyses that typically focus on the relationship between price and quantity.

The concept of food values, developed by Lusk & Briggeman (2009), offers an effective and structured framework for capturing consumer preferences. It enables researchers to identify the fundamental attributes such as naturalness, taste, and origin that influence food choices, including those that are often unconscious or difficult to articulate through direct questioning. To measure consumer preferences for food values, BWS is recommended for its accuracy and efficiency. This method has been widely used in food studies across various regions, including Chinese food markets (e.g., Lockshin et al. 2017, Jin et al. 2019, Jo & Lee 2021, Maruyama et al. 2020, Wu et al. 2024). Data from an original online survey on mung bean purchases conducted in December 2022 were used in the analysis.

Methodology and data

1. Food values and best-worst scaling

The eleven food value attributes developed by Lusk & Briggeman (2009) were selected for their stability over time and their ability to explain consumer choices across various food products (Table 1). These attributes align well with the product characteristics of mung beans in China and were therefore adopted in the online consumer survey for this study. In the survey, "appearance" refers explicitly to the beans themselves rather than the packaging.

The survey included eleven BWS questions designed using the balanced incomplete block design approach. Each question presented five choices among the eleven attributes (Fig. 1). Through the entire survey, each attribute appeared five times. Respondents were asked to choose the most important ("best") and least important ("worst") attributes when purchasing mung beans for home consumption in each question. The creation of the BWS questionnaires and the analysis of the results were conducted using R Core Team (2024) and the support. BWS package (Aizaki & Fogarty 2023).

The number of times that respondent n (n = 1, 2, 3,…N) selected the most important attribute z in eleven questions is denoted as B_{zn} and the number of times that respondent n selected the least important is denoted as W_{zn}. The difference between the two variables represents the B–W score of respondent n, denoted as $BW_{zn} = B_{zn} - W_{zn}$, where the highest possible BW_{zn} is +5 and the lowest is −5. The aggregated scores for all N respondents for attribute z are calculated as $B_z = \sum_{n=1}^{N} B_{zn}$, $W_z = \sum_{n=1}^{N} W_{zn}$, where B_z corresponds to "best," W_z to "worst." The difference is

$$BW_z = B_z - W_z = \sum_{n=1}^{N} BW_{zn},$$

where we can call BW_z "B–W" for attribute z. Using BW_z, we calculate the mean of BW_{zn}, or "mean B–W" as BW_Z/N.

Table 1. Attributes of food values

Lusk & Briggeman (2009)		This study	
Attribute	Description	Attribute	Translation in Chinese (as in the survey)
Naturalness	Extent to which food is produced without modern technologies	Naturalness	天然，无加工或少加工
Taste	Extent to which consumption of the food is appealing to the senses	Taste	味道好
Price	The price that is paid for the food	Price	价格合理
Safety	Extent to which consumption of food will not cause illness	Safety	食品安全
Convenience	Ease with which food is cooked and/or consumed	Convenience	便利性（烹调和食用方便）
Nutrition	Amount and type of fat, protein, vitamins, etc.	Nutrition	有营养
Tradition	Preserving traditional consumption patterns	Tradition	传统或饮食文化
Origin	Where the agricultural commodities were grown	Origin	产地
Fairness	The extent to which all parties are involved in the production of the food	Fairness	公平贸易（生产者、销售者等都能公平获利）
Appearance	Extent to which food looks appealing	Appearance	豆子外形
Environmental Impact	Effect of food production on the environment	Environment	对环境友好

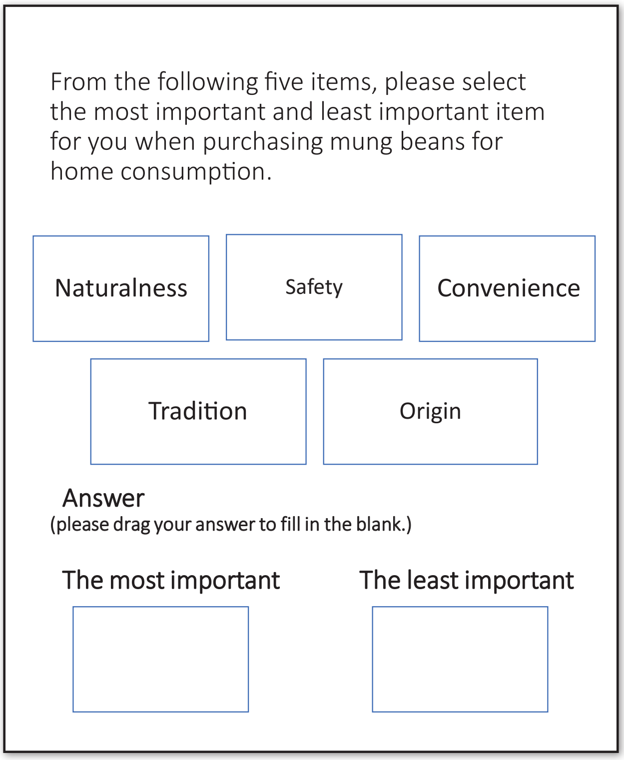

Fig. 1. Sample of BWS questions in the survey

2. Latent class (LC) analysis

To account for heterogeneity in consumer preferences, latent class (LC) analysis is commonly employed in BWS studies. Statistical measures derived from BWS analysis, particularly standard deviations, often reveal substantial individual-level variations within a single dataset. To improve model fit by capturing this heterogeneity, we applied LC analysis to classify respondents into distinct preference-based segments, following the methodologies established by Dekhili et al. (2011) and Lockshin & Cohen (2011).

Population-level B-W scores for each class and prior probabilities for all respondents were estimated using Stata's gsem command with maximum likelihood estimation (Greene 2018). Wald tests, followed by Holm-Bonferroni corrected Z-tests, were conducted to identify differences in B-W scores for each attribute across classes.

For Class j (j = 1, 2, ..., J), we assume that the B-W score of respondent n for attribute z, denoted as BW_{zn}, follows a normal distribution with mean μ_{zj} (i.e., population-level B-W score) and variance σ_{zj}^2. The probability density function of BW_{zn} is thus given by $f(BW_{zn}|Class = j, \mu_{zj}, \sigma_{zj}^2)$. Assuming that BW_{zn} is uncorrelated across attributes, the joint probability density function for all attributes z is $\prod_{z=1}^{11} f(BW_{zn}|Class = j, \mu_{zj}, \sigma_{zj}^2)$.

The prior probability that respondent n belongs to Class j (j = 1, 2, ..., J) is modeled using a logistic function:

$$p(\theta_j) = \frac{\exp(\theta_j)}{\sum_{j=1}^{J} \exp(\theta_j)}$$

where θ_j is a class-specific parameter. The log-likelihood function for the LC model is:

$$log - likelihood = \sum\nolimits_{n=1}^{N} \ln\left[\sum\nolimits_{j=1}^{J} p(\theta_j) \times \prod\nolimits_{z=1}^{11} f(BW_{zn}|Class = j, \mu_{zj}, \sigma_{zj}^2)\right]$$

Since the specific class to which each respondent belonged was unobserved (latent), individual B-W scores were then used to calculate the posterior probability for each respondent. Finally, each respondent was assigned to the class with the highest posterior probability.

3. Data

To explore mung bean consumption practices and purchasing habits, preliminary interviews with a small number of individuals were conducted before the main survey. The insights gained were used to design the questionnaire. Based on this, an online survey was conducted in December 2022 with residents of Beijing, Guangzhou, and Chengdu, with the assistance of Kantar China (https://www.kantar.com/en-cn). Considering China's vast size and regional variations in dietary habits, we strategically chose Beijing in the north, Guangzhou in the south, and Chengdu in the mid-west of the country in order to obtain a representative sample that could illustrate geographical differences in mung bean purchases.[1]

Respondents were drawn from Kantar China's consumer database using quota sampling, based on the age and gender composition of China's urban population. An age range of 20 to 54 was also implemented to target individuals with experience purchasing mung beans. Responses from 900 consumers were collected in the main survey, 836 reported buying beans at least once

[1] All three are mega-cities with populations exceeding ten million and are known for their distinct local cuisines: Beijing cuisine, Cantonese cuisine, and Sichuan cuisine, respectively.

between 2020 and 2022. This suggests that in China, most urban residents have experience purchasing mung beans.

Table 2 summarizes the demographics of the screened sample from 836 respondents. As gender, age and income distribution generally reflect the situation in each city, the sample collected by the online survey is considered effective for showing consumers' preferences.

Results

1. Importance of food value attributes

Results of the best, worst, B–W, and mean B–W scores of each food value attribute are presented in Table 3. To assess whether the observed differences in mean B–W scores were statistically significant, we conducted paired-sample *t*-tests. The results indicate that most attribute pairs exhibited statistically significant differences.

Safety and nutrition have the highest mean B–W scores, at 2.456 and 2.029, respectively. The mean B–W scores for naturalness, taste and environment also show that these attributes positively affect mung bean purchase decisions. Consumers consider price, tradition, fairness, convenience, and origin less important. Appearance was the least important of all the attributes with a mean B–W score of −2.292. The standard deviation in the table indicates the degree of heterogeneity in respondents' preferences. The comparatively high standard deviation for safety, the attribute most valued by consumers in general, needs to be further examined through LC analysis.

Mean B–W scores were also calculated by city (Fig. 2). Paired-sample *t*-tests were conducted for each city to assess differences in mean B–W scores between attribute pairs. In Beijing, the differences between tradition and fairness, and between fairness and convenience, were not statistically significant at the 0.1 level. Similarly, no significant differences were found in Guangzhou and Chengdu between price and tradition, or between fairness and convenience.

The three most important attributes were consistently ranked in Beijing, Guangzhou and Chengdu: safety was first, followed by nutrition and naturalness. Origin and appearance were the least important attributes in all three cities. Spearman's rank correlation coefficients for the mean B-W scores among the cities were 0.99 between Beijing and Chengdu, 0.99 between Beijing and Guangzhou, and 0.98 between Guangzhou and Chengdu. These results indicate that consumers across China have the same tendencies to favor health-related factors while depreciating origin and appearance, as shown in Table 3.

2. Latent segments of consumers

LC analysis was conducted using the B–W scores of respondents from the same sample. Models ranging from two to six classes were estimated (Table 4). The three-class model was adopted in this study for two reasons.

First, although the optimal number of classes is typically determined by the minimum Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, both criteria continuously decreased in this instance, so we evaluated the relative

Table 2. Demographic characteristics of the samples

	Total (N= 836)	Beijing (N= 277)	Guangzhou (N= 277)	Chengdu (N= 282)
Gender				
Male	411	135	137	139
Female	425	142	140	143
Age				
20-29	211	71	69	71
30-39	282	96	90	96
40-49	229	74	78	77
50-54	114	36	40	38
Household Income (yuan/month)				
0-15,000	135	47	30	58
15,001-30,000	439	133	153	153
30,001-45,000	172	60	67	45
45,001-	90	37	27	26

Table 3. Average best-worst scores of attributes that influence consumers' purchase of mung beans (N= 836)

Attribute[a]	Best	Worst	B–W	Mean B–W[b]	Standard deviation[c]
Safety	2240	187	2053	**2.456**	1.993
Nutrition	1888	192	1696	**2.029**	1.708
Naturalness	1285	304	981	**1.173**	1.799
Taste	954	356	598	**0.715**	1.538
Environment	731	613	118	**0.141**	1.684
Price	473	832	–359	–0.429	1.695
Tradition	439	893	–454	**–0.543**	1.722
Fairness	332	987	–655	–0.784	1.625
Convenience	421	1120	–699	**–0.836**	1.796
Origin	204	1567	–1363	**–1.630**	1.702
Appearance	229	2145	–1916	–2.292	2.054

[a] Sorted by mean B–W.

[b] Paired-sample *t*-tests were conducted between each attribute (excluding appearance) and the one ranked immediately below it. Bolded mean B–W scores indicate significance at the 1% level; non-bolded scores are not significant at the 10% level. Testing all possible pairs with multiple comparison adjustments would substantially reduce statistical power, thereby increasing the risk of Type II errors. As this study's research objective did not require examining all possible attribute pairs, the tests were performed without multiplicity adjustments.

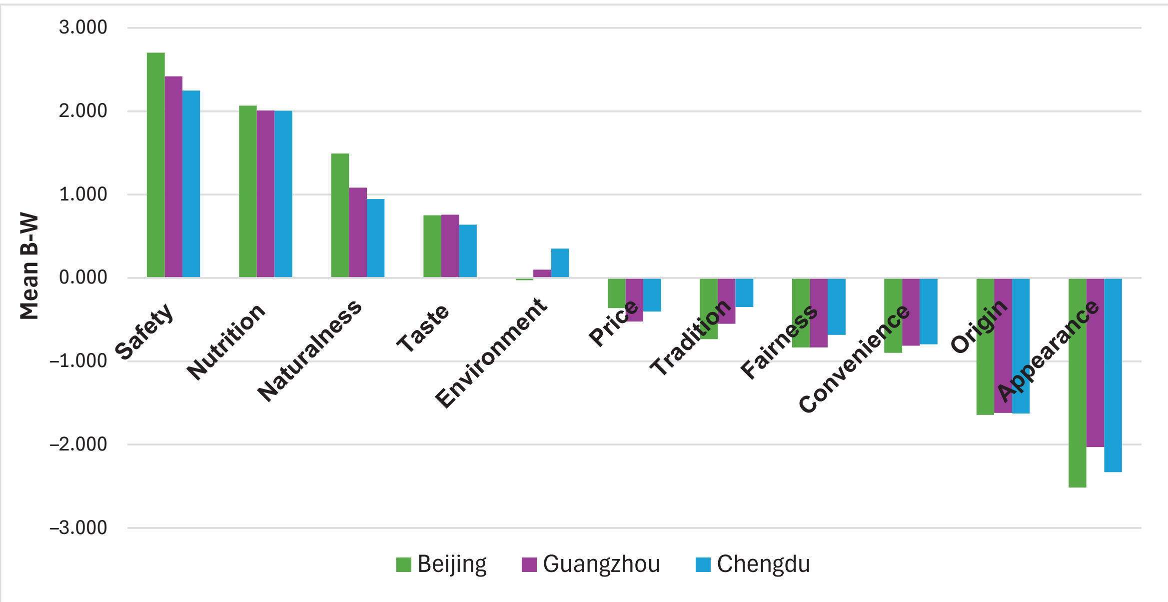

Fig. 2. Average importance of attributes that influence consumers' purchase in Beijing, Guangzhou, and Chengdu
Attributes are sorted according to the data from Beijing.

changes in these indices (ΔAIC and ΔBIC in Table 4) following established methodologies (Sun et al. 2023, Wu et al. 2024). The improvements in model fit beyond the three-class model were deemed negligible, indicating that added model complexity yielded limited benefit. To avoid overfitting, the three-class model was provisionally adopted. Second, the core characteristics of the three-class model demonstrated superior interpretability regarding consumer preferences compared to alternative models. Based on these evaluations, we concluded that the three-class model offered the most efficient and interpretable representation of the observed data.

Estimated B–W scores and p-values for all attributes in the three-class model are shown in Table 5. We also conducted Wald tests to investigate the hypothesis that the B-W scores for each attribute were equal across the three classes. The results show that the hypothesis is rejected ($p < 0.01$ for all attributes). Furthermore, in pairwise comparisons of classes for each attribute, the hypothesis of equality is also rejected in most cases. These results suggest that all attributes are important in segmenting the classes.

Z-tests were conducted to evaluate the differences between the B–W scores of each attribute and the one ranked immediately after it within the same class. The results for selected attribute pairs relevant to this discussion are as follows. In Class 1, the p-value for the difference between environment and safety was 0.04. In Class 2, the p-values for the differences between nutrition and safety, and between price and fairness, were both below 0.01. In Class 3, the p-value for the difference between naturalness and price was also below 0.01.

Unlike the general preferences for safety and nutrition shown in Table 3, the LC analysis revealed three distinct consumer segments. Based on the core attributes of each class, Classes 1, 2, and 3 were named the "environment-friendly group," "safety-first group" and "health-flavor group," respectively. Respondents in the

Table 4. Criteria for determining the optimal number of latent classes

Classes	Log-likelihood	AIC	ΔAIC	BIC	ΔBIC
2	–17794.20	35656.40		35817.17	
3	–17644.05	35380.09	0.77%	35597.61	0.61%
4	–17573.15	35262.30	0.33%	35536.56	0.17%
5	–17519.02	35178.05	0.24%	35509.05	0.08%
6	–17460.94	35085.88	0.26%	35473.63	0.10%

Table 5. Latent class model estimates

Attribute	Class 1 Environment-friendly group		Class 2 Safety-first group		Class 3 Health-flavor group		Wald test
	B–W score[a]	p-value	B–W score[a]	p-value	B–W score[a]	p-value	p-value
Naturalness	0.000	1.000	1.736	0.000	1.440	0.000	0.000
Taste	–0.226	0.024	0.714	0.000	1.623	0.000	0.000
Price	–0.123	0.299	–1.012	0.000	0.168	0.190	0.000
Safety	0.452	0.000	3.304	0.000	3.086	0.000	0.000
Convenience	0.158 [b]	0.167	–1.975	0.000	–0.048 [b]	0.681	0.000
Nutrition	0.434	0.000	2.601 [b]	0.000	2.686 [b]	0.000	0.000
Tradition	0.364	0.001	–0.329	0.000	–1.743	0.000	0.000
Origin	–0.997	0.000	–2.059	0.000	–1.584	0.000	0.000
Fairness	0.009	0.929	–0.339	0.000	–2.227	0.000	0.000
Appearance	–0.806	0.000	–3.114	0.000	–2.463	0.000	0.000
Environment	0.736	0.000	0.472	0.000	–0.937	0.000	0.000

[a] Estimated μ_{zj}. Estimates of σ_{zj} and θ_j are omitted due to space constraints. For further details, contact the corresponding author.

[b] Attributes with no significant differences at the 10% level, based on Holm–Bonferroni corrected Z-tests comparing B–W scores across class pairs.

environment-friendly group (Class 1) placed the strongest emphasis on environment. They also valued safety, nutrition, and tradition over other attributes. For Class 1, the estimated B–W scores fall within a narrow range (0.736 to –0.997), indicating that the differences in the importance of attributes are relatively small compared to that of the other classes. In the safety-first group (Class 2), respondents prioritized safety over other attributes to a large extent compared to the other groups. The low and negative score for price in this group suggests that these consumers are willing to purchase mung beans with a strong safety guarantee, regardless of cost. The health-flavor group (Class 3) was primarily concerned with health benefits (safety and nutrition) and flavor. This group exhibited the strongest preference for taste among all groups. Notably, none of the consumer groups valued origin or appearance.

Table 6 shows the estimated compositions of Classes 1 to 3. Among the 836 samples, Classes 1, 2, and 3 account for 27.3%, 44.9%, and 27.6% of the total, respectively. The *p*-values indicate the probability of testing the null hypothesis that demographic characteristic variables and classifications are independent. At the level of 0.05, factors such as age group, household income, online purchases, and living with children under 15 were statistically significant. City and gender were not statistically significant, suggesting that regional or gender differences do not play a key role in forming consumer segments for mung bean purchases.

Environment-friendly consumers in Class 1 were more likely to be over 50 years old or have moderate household incomes (between 15,001 and 45,000 yuan per month). Consumers who prioritized safety in Class 2 were more likely to belong to high-income families, earning over 45,000 yuan monthly, or households with children under 15 years old. Consumers in Class 3, who emphasized both health and flavor, were more likely to be in their 30s or have lower household incomes. Notably, more than 40% of Class 2 and Class 3 consumers have bought mung beans online, compared with 29.6% in Class 1. This disparity likely reflects the older demographic of Class 1.

Table 6. Classification of classes by city and demographic characteristics (%)

Variable	Class 1 Environment-friendly group	Class 2 Safety-first group	Class 3 Health-flavor group	All samples	*p* -value [a]
	(N= 229)	(N= 376)	(N= 231)	(N= 836)	
City					0.069
Beijing	26.20	34.31	38.10	33.13	
Guangzhou	34.50	33.78	30.74	33.13	
Chengdu	39.30	31.91	31.16	33.73	
Gender					0.131
Male	49.78	45.74	54.11	49.16	
Female	50.22	54.26	45.89	50.84	
Age group					0.000
20-29	22.71	28.19	22.94	25.24	
30-39	26.20	34.31	40.26	33.73	
40-49	27.51	27.92	26.41	27.39	
50-54	23.58	9.58	10.39	13.64	
Household income (yuan/month)					0.043
1-15,000	16.59	12.76	21.21	16.15	
15,001-30,000	50.65	52.93	53.68	52.51	
30,001-45,000	22.27	21.01	18.18	20.57	
45,001-	10.49	13.30	6.93	10.77	
Online purchase	29.69	42.55	42.86	39.11	0.003
Living together with					
Child under 15	43.23	63.83	56.71	56.22	0.000
Elderly over 60	24.89	17.82	17.32	19.62	0.061

[a] *p*-values are used for testing independence.

Discussion, conclusion, and limitations

This study investigated urban Chinese consumers' preferences for mung beans. Based on the BWS analysis results, safety and nutrition ranked highest among all attributes, indicating that healthfulness is the most important aspect influencing consumers' purchase behavior. The emphasis on safety aligns with the findings of previous studies such as Jin et al. (2019) and Sun et al. (2023). Additionally, the positive B–W score for environment shows the high environmental consciousness of Chinese consumers when purchasing mung beans. In contrast, the low score for origin (−1.630) also requires further investigation. No notable differences in consumer preferences were observed across the three cities, suggesting a consistent tendency among consumers to emphasize healthfulness while placing less importance on origin and appearance.

The LC analysis revealed significant heterogeneity in consumers' preferences for mung beans, identifying three distinct consumer segments: the "environment-friendly group," the "safety-first group," and the "health-flavor group." Three key points emerge from the findings of LC analysis.

First, consumers in the safety-first group strongly prioritized food safety, and this preference was particularly pronounced among those with higher household incomes or children under 15 years old. This finding suggests that rising income levels are associated with greater food safety awareness, especially in the context of a declining birthrate, where parents may be more attentive to their children's health and nutrition.

Secondly, in the environment-friendly group, environment emerged as the most valued attribute, followed by safety and nutrition. The demographics of this group merit further discussion, as they offer valuable insights into the characteristics of consumers who do not prioritize safety. These consumers tend to be over 40 years old, shop online less frequently, and are less likely to live with children under 15. They also place greater value on tradition. This indicates that moral cues, such as environmental impacts and the preservation of food culture, can positively influence mung bean demand, particularly among consumers in their 40s and 50s.

Although this study cannot fully explain why consumers prioritize the environmental value of food products, one plausible explanation is the concern over environmental degradation in urban China. Since the early 2000s, urban residents have been increasingly affected by severe air pollution, and the decline in environmental quality may have heightened health concerns, especially among older populations. As Liu et al. (2014) suggest, age has become positively associated with public environmental concern in China since 2007. The age composition of the environment-friendly group in this study supports the idea that older consumers are more attentive to environmental impacts. These findings indicate that in China, health consciousness related to mung bean purchases extends beyond the product's intrinsic quality to encompass the sustainability of the production system.

Thirdly, the results of the LC analysis reaffirmed the minimal significance placed on origin by consumers in general, as none of the consumer groups valued this attribute. This poses a significant challenge to mung bean producers in China. In the international market, mung beans from Jilin and Shaanxi Provinces are well-known for their high quality (Tajima & Zhang 2013). However, in China, most edible bean products display information about packaging facilities and their locations on the package, but not the names or locations of the bean producers. This business practice may be one reason why consumers placed low importance on origin in the survey.

In this survey, approximately 40% of urban consumers reported purchasing mung beans from online vendors. To enhance competitiveness, producers and agribusinesses should promote products online by emphasizing key attributes and raising awareness of production regions to strengthen consumer recognition of product origin.

This study fills the gap in the analysis of China's edible bean market by applying the concept of food values and the best-worst scaling approach. Despite its contributions, this study had several limitations. First, it did not address how food value attributes influence consumers' willingness to pay for mung beans. Secondly, while this study focused on mung bean demand, preferences for processed mung bean products, such as drinks or mooncakes, should be examined to gain a more comprehensive understanding of the mung bean market in China. Finally, as the sample was drawn from three major cities, further research in smaller cities and rural regions is needed to provide a more complete picture of mung bean demand nationwide.

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