To Buy or Not to Buy: A Choice Experiment on Consumers' Preferences for Different Dimensions of Milk Tea Products

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Abstract

Milk tea consumption has been a new fashion in recent years, and now consumers have developed new preferences. In this paper, we conduct an investigation of consumers' preferences towards different kinds of milk tea products and the impact of different attribute combinations to their penchants. Delicately designed online discrete choice experiments were conducted to elicit people's preferences for new milk tea attribute combinations. Following the survey, a general mixed logit model was applied, and parameter estimation was performed to deeply analyze the outcomes. This was followed by a series of data analyses and model tests to validate the results further. Finally, we come to the results that the attributes of "healthy", "environmentally friendly", and "sugar substitute" have emerged as the top three factors most valued by individuals. The result largely contributes to the more focused marketing strategy for milk tea companies.

1. Introduction

"You are my U-Loveit, I will hold you in my hands!" This was Jay Chou's line when he spoke for U-Loveit milk tea. If you look closely, you may find that this fanatical love of Chinese consumers for milk tea seems to have been widespread for a long time. You can easily notice that the young Chinese population always has a cup of aromatic milk tea in their hands, for relaxation after work or happy parties.

However, while China's milk tea market is huge, not all owners are making money. The competition in the milk tea market is very fierce. Some milk tea seems to be always more favored by young people, while some milk tea shops are facing the risk of closure because of the lack of customers. Currently, Xi Cha, Nai Xue's tea, and Misue Ice City are the three most popular milk tea products in China (NCBD, 2024).

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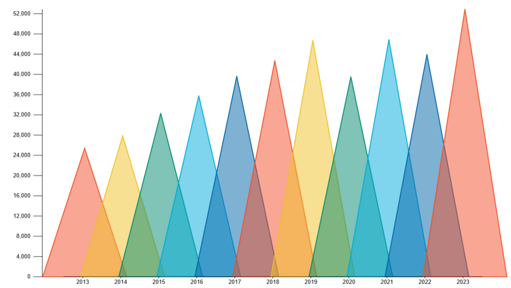


Figure 1. Total revenue of China's catering market from 2013 to 2023 (RMB 100 million).

This led us to wonder: what are consumers' preferences for different dimensions of milk tea products? In this report, we are going to conduct research based on choice experiments to answer this question.

2. Background

Low prices are no longer enough to attract customers, but there is a higher level of pursuit for product quality, and customers pay more attention to their own emotional experience and emotional value needs in the consumption process (贾哲 & 魏志茹, 2022). Starbucks has always been encouraging customers to bring their cups to buy coffee, which not only advocates the concept of environmental protection of the brand but also enables customers to get better prices (武心怡, 2023). The queuing time of customers will directly affect the image of the supermarket in the minds of consumers, and then the image of the customer satisfaction level (奚卫宇, 2008). At the same time, through pre-investigation, we found that the tea base and milk source of milk tea can affect the choice of consumers.

In conclusion, we focus on price, types of milk, types of tea, sugar, ice, waiting time, and environmental sustainability to develop our choice experiment.

3. Factors

As we have mentioned above, we consider the following factors in our choice experiment design.

3.1. Price

As a crucial factor in consumers' purchase decisions, price serves as an external cue for evaluating the quality of milk tea. Additionally, price is a key metric for researchers to calculate consumers' willingness to pay (WTP) (Train, 2009). The key to whether small and medium-sized enterprises can develop smoothly lies in the mastery of two standards, one is quality, and the other is price and brand (王俊琪, 2024).

From the perspective of microeconomics, consumers are flexible to price changes, and once prices change, consumers' preferences will also change greatly. According to the practical situation, we divide the price into three levels: 10.9 yuan, 15.9 yuan, and 20.9 yuan.

3.2. Types of Milk / Tea

As the name suggests, milk tea consists of milk and tea as its two main components. Differences in ingredients can lead to different tastes and also impact health. Using higher quality milk and tea results in better-tasting milk tea and is healthier for the consumer, but it can be more expensive. Therefore, consumers might make trade-offs. According to our preliminary survey, more than half of the respondents are very concerned about the quality of milk and tea.

In this research, we categorize the types of milk as pure milk, skimmed milk, and non-dairy creamer and we categorize the types of tea as high-quality and normal-quality.

3.3. Sugar / Ice

In the modern method of making milk tea, the content of nutrients such as protein is reduced or even zero, and sugar is replaced. And even if the half-sugar and sugar-free milk tea products have been measured by authoritative institutions, they still contain excessive sugar content (狄歌& 雷胜男, 2022). Young consumer groups have a high demand for their own body and often take this into account when choosing milk tea.

Meanwhile, some milk tea shops want to save on ingredients or ensure consistent quality, so they use fixed ratios when making milk tea, which results in non-customizable options. Consumers might not want their drinks too cold or might want more milk tea, thus they sometimes consider ice.

In this research, we categorize the sugar as no sugar, half sugar, full sugar, and sugar substitute (zero calories), and we categorize ice as removable and irremovable.

3.4. Waiting Time

Convenience takes into account the queuing time and store density, making it a significant indicator. On the impact of queuing, there are two explanations. Firstly, consumers usually have a strong sense of time. If a queue is too long, they will give up dining there. Secondly, on the contrary, longer queuing time usually indicates that the store's products are of good quality and attract consumers to eat in the store (代英东, 2019). As a result, in our research, we categorize the waiting time as 15 mins, 30 mins, and 45 mins.

3.5. Environmental Sustainability

Plastic packaging such as plastic bags accounts for about 40% of all plastic products produced, and the use of plastic straws also accounts for a large proportion (李道季, 2019). Environmental sustainability can be reflected in many aspects of the milk tea industry, and whether to use paper straws is a key point for consumers to judge whether a brand is environmentally friendly. However, paper straws can quickly become soggy and lose their structural integrity, especially in cold or hot beverages, making them less practical for consumers. So consumers might make trade-offs.

Therefore, environmental sustainability in our research includes two levels: paper straws and plastic straws.

4. Methods

4.1. Assumptions

To achieve the purpose of our research, we made the following assumptions:

- Consumers seek *utility maximization* (Lancaster, 1966) in their choices.
- Apart from the factors we have listed, there are no other factors that interfere with consumers' decision-making.
- Preferences here are *stated* preferences.

4.2. Survey Design

Before we start handing out our survey, we need to design our survey. The following sections illustrate our survey design from *experiment design* to *choice experiment in survey*.

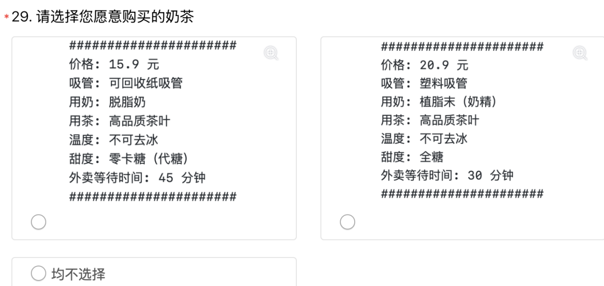
4.2.1. Experiment Design

Considering all the factors and levels we mentioned before, we used a one-step method to design the choice experiment directly by specifying every attribute in each alternative as a factor in the design approach, which reaches a relatively nice balance between the D-efficiency and the number of choice sets. Using `R`, we generated 25 choice sets.

By using `Python` to post-process the choice sets we generated, we can derive 25 choice tasks. Here we are giving one example.

##	A.price	A.conv	A.esg	A.milk	A.tea	A.ice	A.sugar	B.price	B.conv	B.esg	B.milk
## 1	2	3	2	3	2	1	1	1	1	1	3
## 2	1	3	1	2	1	1	2	1	3	1	2
## 3	3	1	1	1	2	1	1	1	1	2	2
## 4	3	3	1	3	1	1	1	3	1	1	1
## 5	1	1	2	3	1	1	2	2	1	2	1
## 6	2	2	1	3	2	1	3	2	1	2	3
## 7	2	1	2	1	1	2	3	3	1	1	2
## 8	2	2	2	1	2	1	2	3	3	1	1
## 9	2	1	2	2	2	1	4	2	2	1	2
## 10	1	3	2	1	2	2	3	1	3	2	3
## 11	2	1	1	3	1	2	3	1	2	1	1
## 12	1	1	2	2	2	2	1	2	3	1	1
## 13	3	2	2	1	1	1	4	1	2	2	1
## 14	2	2	1	3	1	2	1	1	3	2	2

Figure 2. Choice sets generated using R.


*29. 请选择您愿意购买的奶茶

######################
价格：15.9 元
吸管：可回收纸吸管
用奶：脱脂奶
用茶：高品质茶叶
温度：不可去冰
甜度：零卡糖（代糖）
外卖等待时间：45 分钟
######################

######################
价格：20.9 元
吸管：塑料吸管
用奶：植脂末（奶精）
用茶：高品质茶叶
温度：不可去冰
甜度：全糖
外卖等待时间：30 分钟
######################

均不选择

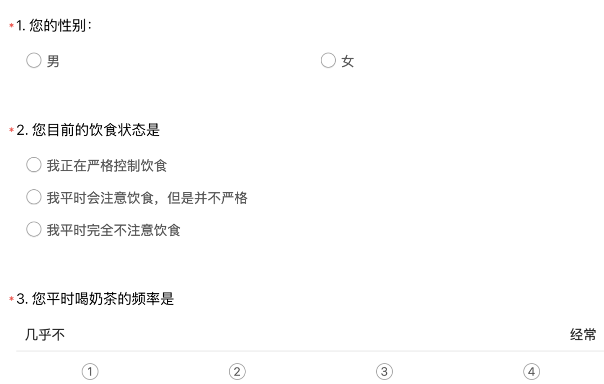
Figure 3. An example of one single choice task.

4.2.2. Choice Experiment in Survey

After deriving all the choice tasks, we designed our survey based on our choice experiment.

Introduction Before our questionnaire started, we briefly introduced our research topic and we guaranteed that we were doing this survey anonymously.

Demographic information The first section of our questionnaire includes questions related to socio-demographic information (Nguyen et al., 2022). We use the information collected to determine the respondent's characteristics.


*1. 您的性别：

男

女

*2. 您目前的饮食状态是

我正在严格控制饮食

我平时会注意饮食，但是并不严格

我平时完全不注意饮食

*3. 您平时喝奶茶的频率是

几乎不 ① ② ③ ④ 经常

Figure 4. Socio-demographic information.

Choice tasks The second section of our questionnaire is a set of choice tasks. To improve the accuracy and efficiency of our questionnaire, we considered the following aspects.

- **Random selection**. Based on the fact that the respondent's patience is limited and a simple observation that the longer the survey is, the lower the possibility for people to fill in the survey accurately is. So, to make the respondent's answer more accurate, we only provide 5 questions for them to answer, by asking the respondent to randomly select one from 5 options that have been shuffled. If the sample size is large enough, we can expect that we will receive the same number of questionnaire *blocks*.

- **Validation/Trap question** The validation/trap question helps eliminate respondents who did not carefully read the survey questions, which would result in poor data quality (Gao et al., 2016; Malone & Lusk, 2019). In our practice, we go even one step further: By adding the first question again to the end of the questionnaire, we want to see if this respondent has a consistent preference and if the respondent chooses the same option, we are assuming that this respondent confidently and accurately answered our questions. Otherwise, we are assuming that this respondent is not consistent when he/she is choosing milk tea products or he/she is randomly selecting in our experiment.

- **Random order** By providing the options in a random order, we are eliminating the possibility that some people may prefer to choose Option A without considering the content.

Suggestion The third section is designed to collect the respondents' suggestions or preferences on milk tea products, trying to find out what factors we may have not taken into account. Word-cloud analysis based on word frequency gives us the following result.

Figure 5. Word-cloud analysis.

Our full questionnaire is available in the appendix. We collected our data by uploading our questionnaire to 问卷星 platform.

4.3. Econometric methods

In this study, comprehensive econometrics were taken to construct, analyze, and evaluate. To decompose our work clearly, the process involved three main phases: model construction, model analysis, and model evaluation.

4.3.1. MODEL CONSTRUCTION

The initial phase focused on model construction, starting from data transformation. Raw data processing was undertaken to clean and normalize the dataset, preparing for subsequent analysis. Categorical data required the creation of dummy variables through manual coding, converting these into binary indicators for use in regression models and allowing for the spontaneous choice of the base category.

Here, the appliance of the trap question divides the respondents into two subcategories: the "Fail Group" and the "Pass Group". Scale parameter estimation was performed using the conditional logit model to analyze two categories across all respondents. The Swait & Louviere, 1993 method provides a sophisticated approach for addressing scale heterogeneity in discrete choice models, particularly useful when comparing choice data across subgroups.

In contexts where respondents are divided into categories such as the "Fail Group" and "Pass Group," understanding whether these groups exhibit different scales of utility can significantly enhance model accuracy and interpretability. The key step is looping through a set of values for θ_2, typically ranging from 0.5 to 2 in small increments. For each value of θ_2, the utility function for the "Pass Group" is adjusted by dividing their utility components by θ_2. The adjusted utility functions for group one remain

$$\text{Group 1: } U_{ij} = \beta' X_{ij} + \varepsilon_{ij}^{1}$$

while the other group, they are scaled as

$$\text{Group 2: } \frac{U_{ij}}{\sigma_2} = \theta_2 \alpha^{'} X_{ij} + \theta_2 \varepsilon_{ij}^{2}$$

The log-likelihood function for the combined data set with the adjusted utilities is then calculated and maximized concerning θ_2.

$$LL(\theta_2) = \sum_{i \in \text{Fail Group}} \log P_i + \sum_{j \in \text{Pass Group}} \log P_j \left(\frac{1}{\theta_2} \right)$$

Additionally, a Generalized Mixed Logit Model (GMLM) was applied, leveraging the manually created dummy variables to account for unobserved heterogeneity and provide a robust framework for analyzing choice data. The theorem base of this choice experiment model can be traced back to Lancaster's *utility maximization theory* (Lancaster, 1972) and the *random utility theory* (Mcfadden, 1974). The GMLM effectively combines the benefits of the mixed logit model and the scaled multinomial logit model, it captures heterogeneity in preference parameters, allowing for individual-specific tastes and preferences, and addresses heterogeneity in the scale parameters, accounting for variations in decision-making consistency across individuals. Based on the random utility framework, the utility of an individual i associated with the choice alternative j in the situation t can be specified as $U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \beta_i' X_{ijt} + \varepsilon_{ijt}$, Where β_i can be specified to illustrate the heterogeneity in preference parameters and individual variance.

In our study here, the forum is specified to be Where $Price_{ijt}$ is the price of the milk tea alternative j in the choice set t; vector X denotes the remained non-price attributes of j. Moreover, ε_{ijt} is an error component that follows the Gumble distribution.

4.3.2. MODEL ANALYSIS

The second phase, model analysis, involved a detailed examination of willingness to pay (WTP).

In the context of analyzing consumer preferences for milk tea, the price coefficient, α_1, is estimated as a nonrandom parameter. This approach is predicated on the understanding that a normal distribution's density on both sides of zero could lead to unrealistic scenarios, such as upward-sloping demand curves (Hensher et al., 2005b; Sarrias Jeraldo, 2016).

By treating the price coefficient as nonrandom, the model ensures that the willingness to pay (WTP) estimates for various milk tea attributes follow a normal distribution. This approach avoids the unrealistic WTP distributions that can result from the ratio of two random variables (Carson & Czajkowski, 2019). Consequently, the price coefficient can be interpreted as the *marginal utility of money* (Onozaka & Mcfadden, 2011).

Comparatively, the coefficients for non-price attributes are defined as random parameters with a normal distribution. In this specification, β represents the vector of estimated conditional means. The matrix L is a lower triangular matrix used to compute the covariance of the random parameters, and γ_i is a random term following a standard normal distribution. The term γ_i captures the variation in consumer preferences for different attributes of milk tea, reflecting the heterogeneity in tastes and preferences across the consumer base (Hensher et al., 2005a).

Then, both individual and aggregate WTP were determined, with analysis focused on estimating the monetary value respondents placed on different attributes. A comparative analysis between the WTP space and preference space was conducted to understand how respondents' preferences translated into their willingness to pay. This comparison provided valuable insights and highlighted key differences.

In the preference space approach

$$U_{ijt} = \alpha_0 NONE + \alpha_1 Price_{ijt} + \beta_i' X_{ijt} + \varepsilon_{ijt},$$

the parameters β reflect the relative importance of each attribute. However, interpreting the results in monetary terms requires converting these preference parameters into WTP measures, typically by dividing the attribute coefficient by the price coefficient. In particular, the WTP for the attribute k of a milk tea product is $WTP_{i,k} = -\frac{\beta_{ik}}{\alpha_1}$.

The distribution of $WTP_{i,k}$ is derived from the expected distribution of $\hat{\beta}_{ik}$ and $\hat{\alpha}$, as outlined by Train, 2009. In this model, the price coefficient remains constant; therefore, the distribution of willingness to pay (WTP) for each attribute that is not differentiated by price level corresponds to the distribution of the attribute's coefficient. Consequently, the mean and standard deviation of the WTP for each attribute level are estimated like that of the random parameters of the non-price attributes.

$$\text{Mean}(WTP_{i,k}) = -\frac{\text{mean}(\widehat{\beta}_{ik})}{\widehat{\alpha}_1}$$

$$\text{Standard Deviation}\,(WTP_{i,k}) = \frac{\text{SD}(\widehat{\beta}_{ik})}{\widehat{\alpha}_1}$$

In the WTP space approach, the utility function is reformulated to directly estimate the WTP for each attribute.

$$U_{ijt} = \alpha \cdot P_{ijt} + \sum_k \lambda_k \cdot \left(\frac{X_{ijt}^k}{\alpha} \right) + \varepsilon_{ijt}.$$

Here, λ_k is the WTP parameters, which indicate the amount of money an individual is willing to pay for a unit change in attribute k. P_{ijt} is the price of alternative j. In WTP space, the model directly estimates the monetary value of each attribute, avoiding the need for post-estimation calculations. This approach simplifies the interpretation of results, as the coefficients represent WTP values directly. Preference space allows for more flexibility in capturing complex preference structures, while WTP space focuses on economic interpretation.

Furthermore, the probability of each individual choosing each option (P_{ij}) was calculated, offering a clear understanding of the choice probabilities and their determinants within the model. The probability of an individual i choosing alternative j in a sequence of t choices is given by:

$$\begin{aligned} P_{ijt} &= Pr[y_{it} = j] \\ &= \int \frac{\exp(a_0 NONE + a_1 Price_{ijt} + \beta_i' X_{ijt})}{\sum_{t=1}^{T} \exp(a_0 NONE + a_1 Price_{ijt} + \beta_i' X_{ijt})} \\ &\qquad \tau(\beta_i/\beta) d\beta_i \end{aligned}$$

In this context, the term β_i can be heteroskedastic and correlated across alternatives, which necessitates integrating this randomness. The notation $\tau(\beta_i/\beta)$ represents the joint distribution, and β is the distribution parameter of the corresponding attributes. Due to the heteroskedasticity and correlation of β_i across alternatives, this integral does not have a closed form (Hensher & Greene, 2003). Therefore, it is approximated through simulation methods (Hensher et al., 2005a). The parameters in the ML model can be estimated using maximum simulated likelihood. In this case, we used `R` to estimate the mixed logit models using 100 Halton draws.

4.3.3. Model Evaluation

The final phase, model evaluation, employed several metrics to assess model performance. McFadden's R^2 and its adjusted version were calculated to gauge the goodness-of-fit, indicating how well the model explained the observed choices. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare models, balancing model complexity and fit to identify the most parsimonious model. Then, a log-likelihood ratio test was also performed, comparing the generalized mixed logit model (GMLM) with the conditional logit model (CLM) to evaluate whether the additional complexity of the GMLM significantly improved the model fit.

5. Results

5.1. Parameter Analysis

For two separated categories, because both ε_{ij} and θ_2 follow i.i.d. standard Gumbel distribution, and utility is not affected by the scales, we can estimate the model by combining the two data sources together into matrix $\beta' \left[{X_{ij} \atop \theta_2 X_{ij}} \right]$.

To estimate the parameter, we can use Swait and Louviere's tools: loop through a set of values of θ_2, in the conditional logit model, choose the θ_2 that maximizes likelihood.

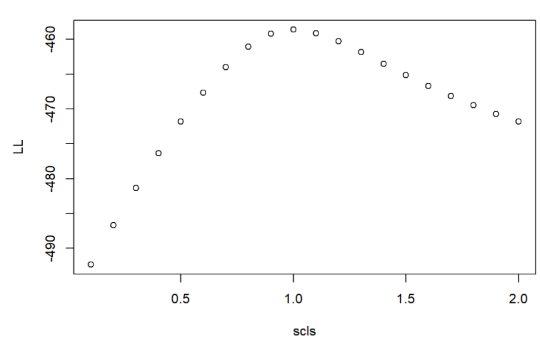


Figure 6. Estimating the scale parameter.

The figure demonstrates that as θ_2 varies, the log-likelihood initially increases, peaks, and then starts to decline. The optimal value of θ_2 is where the log-likelihood is maximized, representing the best scaling factor for the combined data. This optimal θ_2, which is 1.0 in this study, ensures that the utility model appropriately accounts for the differences in scale between the respondent groups.

5.2. Generalized Mixed Logit Model (GMLM)

Due to the limitation of the database, the outcome of regression is not that prominent but still reveals some important tendencies in people's preferences. The following are results in preference space and WTP space respectively. The results in Table 1 depict the coefficient of each alternative, while the omitted ones are chosen as base categories. The coefficient of price is statically prominent and the sign is negative, indicating a reverse price-demand relationship. Comparing the attribute "Full sugar" which has a coefficient of -0.92 and the "Sugar Substitute" option with a coefficient of 0.60, we can conclude an increasing health concern, as people are more willing to choose products with less sugar or sugar substitute without any calories.

Table 1. The results of factories in GMLM.

Vars.	Mean parameters		S.D. of mean para.	
	Coeff.	Std. err.	Coeff.	Std. err.
none	-3.45	0.59		
Price	-0.08	0.03	0.02	0.25
Cov2	0.34	0.24	0.02	0.76
Cov3	-0.36	0.22	0.09	0.76
Esg2	-0.18	0.19	0.06	0.22
Milk2	-0.69	0.23	0.01	0.95
Milk3	-1.47	0.25	0.00	0.59
Tea2	-0.85	0.19	0.09	0.60
Ice2	-0.37	0.25	0.10	0.61
Sugar2	-0.30	0.34	0.08	0.64
Sugar3	-0.92	0.29	0.06	0.61
Sugar4	0.60	0.29	0.26	0.49
τ	0.25	0.37		
γ	11.33	20.12		

Log Likelihood: -444.64, 100 draws.

At the individual level, we carry out the comparison between preference level and WTP space level in Table 2 on the next page, which illustrates the analysis more directly. Here we can see, that Sugar3 and Sugar4 have the minimum and maximum values respectively, indicating a strongly differentiated WTP: People have the average tendency to pay 11.06 yuan for healthier sugar substitutes while need to be paid -28.33 yuan to accept the full-sugar product. However, it also reveals some attributes have high variance in their WTP, which is worth further investigation. In this study, the outcome in WTP space and Preference space vary greatly, which is largely the limitation of a small database.

Certain variables (e.g., Milk3, Tea2) have large standard deviations, indicating that individuals vary more in their willingness to pay for these characteristics. Negative means for certain variables (e.g., Sugar2) indicate that individuals are unwilling to pay more for these characteristics or even want to be compensated.

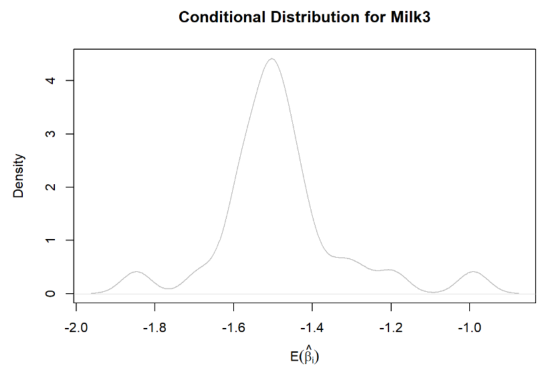


Figure 7. Conditional Distribution for Milk3

5.3. Probability analysis: Individual Level

In comparison to the overall circumstance, we focus more on the individual level to learn about the variance. The probability of individual i choosing the alternative j is then calculated in the following format, the 250 more rows are omitted due to the page size limitation. In this way, more detailed and focused advertisement and marketing strategies can be applied to the focused person and reach the maximum profit in the digital era.

Table 3. Individual Analysis (P_{ij} Outcome)

RID	Set	Alt	choice_prob
1	1	1	0.01570306
1	1	2	0.00645577
1	1	3	0.97784117
1	2	1	0.02161100
1	2	2	0.12412161
1	3	1	0.61407039
1	3	2	0.16430411
1	3	3	0.03358059
1	4	1	0.80238530
1	4	2	0.05253221

250 more rows.

Table 2. Evaluation results

Vars.	Preference Space			WTP Space		
	Mean WTP	Rank	95% CI	Mean WTP	Rank	95% CI
Cov2	5.85	3	(0.24, 11.46)	0.10	3	(-0.04, 0.24)
Cov3	-6.06	6	(-11.26, -0.86)	-0.51	6	(-0.55, -0.47)
Esg2	-3.36	4	(-8.38, 1.66)	-0.47	5	(-0.53, -0.41)
Milk2	-11.41	8	(-20.66, -2.16)	-0.62	7	(-0.70, -0.54)
Milk3	-24.69	9	(-44.18, -5.20)	-1.51	10	(-1.61, -1.41)
Tea2	-14.10	7	(-29.29, -2.91)	-0.86	8	(-0.92, -0.80)
Ice2	-5.89	5	(-10.90, -0.88)	-0.35	4	(-0.41, -0.29)
Sugar2	8.49	2	(1.35, 4.43)	0.30	2	(0.28, 0.32)
Sugar3	-28.33	10	(-60.76, 4.10)	-0.89	9	(-1.05, -0.73)
Sugar4	11.06	1	(0.43, 21.69)	0.69	1	(0.59, 0.79)

5.4. Model Evaluation

The following essential part is evaluating the performance of our models, which involves employing several metrics, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and McFadden's R². These criteria provide insights into model fit and complexity. In addition to these metrics, the log-likelihood ratio test is used to compare two nested models to determine if the more complex model significantly improves the fit. The evaluation process highlights whether the more complex generalized mixed logit model (GMLM) significantly enhances model fit compared to the simpler conditional logit model (CLM). A low p-value in the log-likelihood ratio test indicates a significant improvement, justifying the use of the GML. These comprehensive evaluations ensure the selection of the most appropriate model for analyzing consumer preferences in the context of milk tea attributes, providing robust insights into model performance and fit.

Table 4. Model Statistics

Statistic	Value
Log-likelihood (Model)	939.2752
Log-likelihood (Null)	1044.64
McFadden's R^2	0.1523716
Adjusted McFadden's R^2	0.1028069
Log-likelihood ratio (LR)	27.95885
Degrees of freedom difference (df_diff)	13
p-value	0.009170173

6. Conclusion

Based on the frequency analysis conducted, it is evident that in all data samples, the attributes of "healthy", "environmentally friendly", and "sugar substitute" have emerged as the top three factors most valued by individuals. The significance of these attributes reflects modern society's increasing concern for nutritional well-being, environmental sustainability, and dietary preferences.

The correlation between the degree of environmental protection and consumer purchasing tendencies underscores a growing preference for products with environmentally friendly credentials. Conversely, there exists a complex relationship between sugar content and consumer purchasing behavior. While full sugar content has shown a negative correlation with purchasing propensity, products incorporating sugar substitutes have demonstrated a positive correlation.

These findings suggest that milk tea establishments can adapt their offerings to align with consumer preferences, such as focusing on higher-quality ingredients and developing biodegradable packaging options. However, it is important to note that our study faces certain limitations such as sample size constraints and demographic biases which may impact the universal applicability of our conclusions.

Moving forward, further research should encompass broader demographics to ensure more comprehensive insights into consumer behavior. Additionally, consideration should also be given to potential correlations between attributes to develop an algorithm capable of capturing these complexities while maintaining practicality.

While acknowledging these challenges encountered during our study process including questionnaire design flaws due to fractional factorial design methodology limitations, we remain optimistic about the prospect of refining our algorithms through continued exploration. With dedication and persistence in our pursuit of knowledge discovery beyond this study's conclusion will undoubtedly contribute toward creating more accurate models yielding universally applicable conclusions worthy of further academic investigation.

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A. Survey

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