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Article

A Study on the Tea Drinking Habits of American Consumers and Nutritional Health Guidance

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Abstract: Tea consumption in the United States reflects low-sugar beverage substitution, functional drink selection, and daily dietary management. Drinking habits are influenced by age, consumption scene, tea preference, brewing method, product labels, added sugar, and caffeine tolerance. This study established a multi-source framework for collecting and evaluating American consumers' tea drinking habits and encoded drinking frequency, tea type, brewing temperature, steeping time, serving volume, added sugar, label information, and caffeine sensitivity. The dataset comprised 1,200 adult questionnaires, 36 retail product labels, and 24 prepared-tea samples. Behavioral indicators were cross-analyzed by age, drinking scene, product form, and special-condition risk level for health adaptation. Questionnaire analysis showed that consumers aged 18--29 favored cold-brewed and ready-to-drink tea, whereas participants aged 45 and above paid greater attention to low-sugar and low-caffeine information; high-risk proportions reached 43% among respondents requiring glucose control and 37% among those reporting sleep effects. Label analysis showed that bottled flavored tea contained 13.7 g added sugar per 200 mL on average, compared with 4.2 g in juice- or syrup-containing cold brews. Component testing showed that fresh-brewed green tea contained 148.6 mg polyphenols and 18.4 mg theanine per 200 mL, while black tea contained 42.7 mg caffeine. These findings support age-stratified tea selection, sugar control, caffeine management, and nutrition guidance.

Keywords: American consumers; Tea drinking habits; Nutrition and health guidance; Behavioral portrait

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1. Introduction

Tea consumption in the United States is closely related to healthy beverage choices, with hot tea, cold-brewed tea, bottled tea and functional tea widely consumed at home, in offices, restaurants and fitness settings. Previous studies have shown that artificial intelligence and machine learning technology can be used for individualized nutrition recommendation, and can improve the adaptability and interpretability of dietary recommendations [1]. The research on nutrition recommendation based on the combination of deep generative model and language model provides technical reference for beverage selection, intake restriction and health suggestion generation [2]. The verification of intelligent nutrition recommendation system based on cuisine data shows that dietary cultural differences, food combinations and nutritional goals can be included in the unified computing framework [3]. The dietary recommendation framework integrating machine learning and natural language processing can process dietary records, preference information and health needs, and provide method support for tea label parsing and consumption portrait construction [4]. The review of food recommender systems further points out that the recommendation model should integrate user behavior, nutritional attributes and scenario constraints to improve the practical usability of health recommendations [5]. However, existing studies focus on nutrition recommendation frameworks and provide limited explanation of how tea behavior, label information, measured components and tolerance affect health guidance. Therefore, this paper integrates 1,200 questionnaires, 36 product labels and 24 tea samples, and conducts variable screening, behavioral indicator construction, nutrient intake calculation, component testing and risk classification. It compares age groups, drinking scenarios and tea categories, explains preference differences, and develops guidance for tea selection, sugar control, caffeine management and intake adjustment.

2. Sources of Data on Tea Consumption and Basis of Nutrition and Health Assessment in the United States

The data of tea consumption in the United States are derived from adult questionnaires, dietary recall records, retail product labels, online purchase records and test results of freshly brewed-tea. The nutritional and health evaluation of tea consumption is usually supported by drinking frequency, single consumption volume, tea type, brewing condition, added sugar content, caffeine intake, tea polyphenol supply and individual tolerance level. After variable screening, group coding, outlier elimination and standardization, tea consumption data can form comparable behavioral portraits [6]. The evaluation process also needs to incorporate total daily energy, dietary structure, beverage substitution relationship, and label readability, so that tea drinking recommendations are consistent with actual life situations. Combined with age groups, drinking scenarios, product forms and health concerns, the differences in low-sugar control, caffeine management and active ingredient supply among sugar-free tea, bottled tea, cold-brewed tea, milk tea and functional tea can be further judged, which provides reliable data basis for subsequent ingredient detection, risk classification and tea drinking guidance.

3. Multi-Source Data Integration and Tea Behavior Analysis

3.1. Methods for Data Collection and Analysis of Tea Drinking Habits of American Consumers

The dataset combined 1,200 valid adult questionnaires, matched 24-hour recalls, 36 U.S. retail tea labels, online purchase records, and 24 prepared-tea samples. Questionnaires recorded age, scene, frequency, serving size, tea type, sugar addition, caffeine sensitivity, health concern and label use. The 1,200 responses were divided into four age groups and cross-tabulated with tea form and drinking scene. Respondents aged 18--29 particularly favored cold-brewed and ready-to-drink products, whereas those aged 45 and above more often selected low-sugar or low-caffeine options. Label coding showed bottled flavored tea averaged 13.7 g added sugar per 200 mL, while juice- or syrup-containing cold brews averaged 4.2 g. The 24 tea samples were subsequently used for component testing and intake conversion. The variable screening scores are as follows:

$$R_j = \alpha D_j + \beta C_j + \gamma L_j \quad (1)$$

Equation (1) was used only for data-quality screening, not prediction. R_j denotes the screening score for variable j, and D_j, C_j, and L_j represent completeness, nutritional correlation, and label traceability; α, β, γ are weights summing to one. After screening, the retained questionnaire variables produced the special-condition distribution used in Figure 3: high-risk shares were 26% for caffeine sensitivity, 37% for sleep disturbance, 43% for glucose-control needs, 21% for pregnancy, and 22% for low tolerance among older adults, respectively. Table 1 summarizes the source, scale, retained variables, and analytical role of each dataset.

Table 1. Sample Source and Variable Screening Table of Tea Consumption in the United States

Data Source	Main Variables	Record Scope	Nutritional and Health Function	Screening Method
Adult questionnaire	Drinking frequency and drinking scenario	1,200 samples	Reflects differences in daily tea	Completeness screening

			drinking behavior	
Dietary recall records	Single drinking volume and added sugar	24-hour records	Estimates sugar intake and beverage substitution relationship	Intake conversion
Product label data	Sugar, caffeine and ingredient information	36 types of tea beverage products	Supports label interpretation and risk indication	Label coding
Fresh-brewed tea testing records	Tea polyphenols, caffeine and theanine	24 groups of tea samples	Evaluates active ingredient supply level	Indicator standardization
Online purchase records	Tea type and consumption preference	Order and review data	Identifies tea beverage selection tendency	Categorical variable coding

3.2. Setting of Consumption Frequency and Drinking Scene Behavior Indicators

In order to improve the comparability of the analysis of American consumers 'tea drinking habits, it is necessary to convert drinking frequency, scene type, single consumption amount, tea form and drinking time into unified behavioral indicators, and construct scene-based features that can be used for nutrient intake calculation. In this paper, the number of tea consumption per week and the amount of single consumption are used as continuous variables, and the scenarios of home, office, catering, fitness and commuting are given weights to form the consumption frequency index. The frequency intensity can be written as follows:

$$\mathrm{BI_i} = \frac{\mathrm{f_i} \times \mathrm{v_i}}{\mathrm{V_0}} \# \qquad (2)$$

Where, $\mathrm{BI_i}$ is the frequency intensity of tea drinking, $\mathrm{f_i}$ is the weekly drinking frequency of type i tea, $\mathrm{v_i}$ is the single drinking amount, and $\mathrm{V_0}$ is the standard drinking amount. After completing the frequency processing, the scene-weighted behavior index is further constructed:

$$\mathrm{SI_i} = \sum_{k=1}^{m} \mathrm{w_k}\, \mathrm{p_{ik}} \mathrm{BI_i} \qquad (3)$$

Where, $\mathrm{SI_i}$ is the scene weighting index, $\mathrm{w_k}$ is the scene weight of the k TH category, $\mathrm{p_{ik}}$ is the proportion of tea drinking in this scene, and m is the number of scenes. This setting can transform the differences of tea consumption times, drinking volume and scene into comparable behavior characteristics, provide unified input for subsequent tea preference analysis, nutrient intake calculation and health adaptation verification, and enhance the stability of stratified evaluation results of different age groups. See Figure 1 for the setting of consumption frequency and drinking scene behavior indicators.

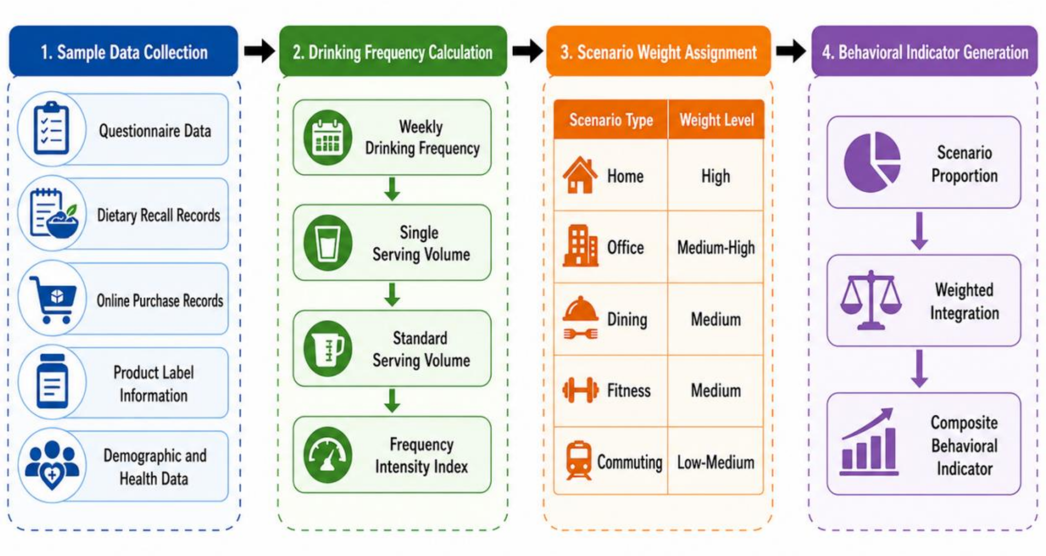

Figure 1. Schematic Diagram of Consumption Frequency and Drinking Scene Behavior Indicator Setting

3.3. Tea Preference and Brewing Method Nutritional Intake Calculation

After the selection of tea consumption sample variables, it is necessary to further calculate the intake level of nutrients under different tea preferences and brewing methods [7]. American consumers drink tea in a variety of forms, including bag-infused black tea, fresh-infused green tea, herbal tea, bottled flavored tea, and readymade cold tea. The amount of tea, steeping time, water temperature, and product ingredients will change the intake of tea polyphenols, caffeine, and sugar [8]. Suppose that the single consumption amount of the ith consumer in the type c tea beverage is Vic, the nutrient concentration per unit volume of the tea beverage is Rc, and the daily intake frequency is Fic, then the basic nutrient intake can be expressed as follows.

$$\mathrm{N_{ic}} = \mathrm{V_{ic}} \times \mathrm{R_c} \times \mathrm{F_{ic}} \quad (4)$$

Where, $\mathrm{N_{ic}}$ is the daily nutrient intake of type c tea for the ith consumer, $\mathrm{V_{ic}}$ is the amount consumed in a single session, $\mathrm{R_c}$ is the concentration of components, and $\mathrm{F_{ic}}$ is the daily intake frequency [9]. Due to the influence of brewing temperature, soaking time and sugar-adding behavior, the brewing correction coefficient is further introduced:

$$\mathrm{A_{ic}} = \mathrm{N_{ic}} \times \mathrm{K_t} \times \mathrm{K_s} \times \mathrm{K_g} \quad (5)$$

Where, $\mathrm{A_{ic}}$ is the actual intake after correction, $\mathrm{K_t}$ is the temperature coefficient, $\mathrm{K_s}$ is the soaking time coefficient, and $\mathrm{K_g}$ is the correction coefficient of adding sugar or ingredients. Tea polyphenol intake, caffeine exposure, and sugar load can be compared when green tea, black tea, and bottled tea form different $\mathrm{A_{ic}}$ values under different scenarios [10].

3.4. Feature Extraction of Tea Drinking Preference and Health Concern under Age Stratification

In order to depict the differences in tea preference among American consumers of different ages, this paper divided the samples into 18-29 years old, 30-44 years old, 45-59 years old and 60 years old and above, and extracted indicators of tea choice, drinking scene, degree of sugar addition, caffeine tolerance and health concern. Let the standardized value of the r-th feature in the a-th age group be Xar and the weight be ωr, then the comprehensive feature score can be expressed as follows:

$$\mathrm{H_a} = \sum_{r=1}^{p} \omega_r \mathrm{X_{ar}} \#(6)$$

Where, $\mathrm{H_a}$ is the tea drinking attention score of the a age group, p is the number of features, $\mathrm{X_{ar}}$ is the standardized feature value, and ω_r is the index weight. Table 2 presents the age-stratified feature extraction Settings.

Table 2. Feature Extraction Table of Tea Drinking Preference and Health Concern under Age Stratification

Age Group	Main Tea Drinking Preferences	Key Extracted Features	Health Concern Focus
18–29 years old	Cold-brew tea, bottled tea, flavored tea	Drinking scenario, added sugar, purchase frequency	Sugar load and label interpretation
30–44 years old	Black tea, green tea, functional tea	Office drinking, caffeine tolerance, tea type selection	Refreshing demand and intake control
45–59 years old	Unsweetened tea, fresh-brewed tea, herbal tea	Drinking time, brewing method, health concern	Active ingredient supply and drinking regularity
60 years old and above	Low-caffeine tea, herbal tea, light tea	Single drinking volume, sensitivity response, label attention	Tolerance risk and drinking safety

Table 2 shows that age stratification connects tea drinking preference, intake and health concerns, which provides a basis for interpretation and stratification of the results.

4. Testing of Nutritional Components and Verification of Health Adaptation of Tea

4.1. Analysis of Test Results of Active Components in Typical Teas

Twenty-four tea samples, including fresh-brewed green, black, oolong, herbal, bottled unsweetened, and bottled flavored tea, were analyzed after converting all results to 200 mL. Fresh infusions were prepared with the recorded tea mass, water temperature, and steeping time. Total polyphenols were determined by Folin--Ciocalteu colorimetry according to ISO 14502-1 [4]; caffeine was quantified by HPLC following ISO 14502-2 [5]; and theanine was measured by HPLC according to ISO 19563 [6]. Added sugar for packaged products was transcribed from U.S. Nutrition Facts labels and standardized to 200 mL, while freshly brewed samples were treated as containing no added sugar unless sugar was recorded during preparation. Fresh-brewed green tea averaged 148.6 mg polyphenols and 18.4 mg theanine per 200 mL, black tea averaged 42.7 mg caffeine, and bottled flavored tea showed lower active-component concentrations than fresh brews. Table 3 reports overall category means.

Table 3. Measured Active-Component Concentrations in Typical Tea Beverages

Tea Beverage Type	Tea Polyphenol Content (mg/200 mL)	Caffeine Content (mg/200 mL)	Theanine Content (mg/200 mL)
Fresh-brewed green tea	148.6	28.5	18.4
Fresh-brewed black tea	112.3	42.7	9.6
Fresh-brewed oolong tea	126.8	34.5	12.7
Herbal tea	22.4	0.3	1.8
Bottled unsweetened tea	76.5	31.2	6.4
Bottled flavored tea	41.8	24.6	3.2

4.2. Comparison of Nutritional Differences and Sugar Load of Multiple Types of Tea

To make the two composite scores reproducible, all components were converted to 0--1. For tea category g, sugar load index was calculated as mean sugar per 200 mL divided by the maximum sugar value among the 36 labels. Accordingly, the sugar load index for each tea category can be expressed as follows:

$$SLI_g = \frac{\bar{S}_g}{S_{\max}} \tag{7}$$

Where, SLI_g is the sugar load index of class g tea; $\bar{S}_g$ is the average sugar content per 200 mL of the product; $S_{\max}$ is the maximum value of sugar content per 200 mL of 36 product labels.

$$X_g^* = \frac{X_g - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

Where, X_g^* is the normalized value of index X ; X_g is the original measured value of class g tea; $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of all tea categories, respectively.

$$NAI_g = 0.35P_g^* + 0.20T_g^* + 0.20C_g^* + 0.25\left(1 - SLI_g\right) \tag{9}$$

Where, NAI_g is nutritional fitness index; P_g^* is the normalized value of tea polyphenols; T_g^* is theanine normalized value; C_g^* is the caffeine suitability normalized value.

The nutritional adaptation index combined min--max normalized polyphenol, theanine, caffeine-suitability, and inverse sugar-load scores using weights of 0.35, 0.20, 0.20, and 0.25, respectively. Caffeine suitability was scored against the study's tolerance thresholds, and all weights summed to one. Applying the same rule to every category yielded sugar-load/nutritional-adaptation pairs of 0.02/0.92 for fresh-brewed unsweetened tea, 0.05/0.84 for bottled unsweetened tea, 0.03/0.78 for herbal tea, 0.18/0.66 for cold-brew tea, and 0.74/0.39 for bottled flavored tea. Bottled flavored tea averaged 13.7 g added sugar per 200 mL, about 54.8 kcal and 27.4% of the 50 g daily reference [7]. Juice- or syrup-containing cold brews averaged 4.2 g. Figure 2 therefore reflects measured inputs and a stated calculation rule.

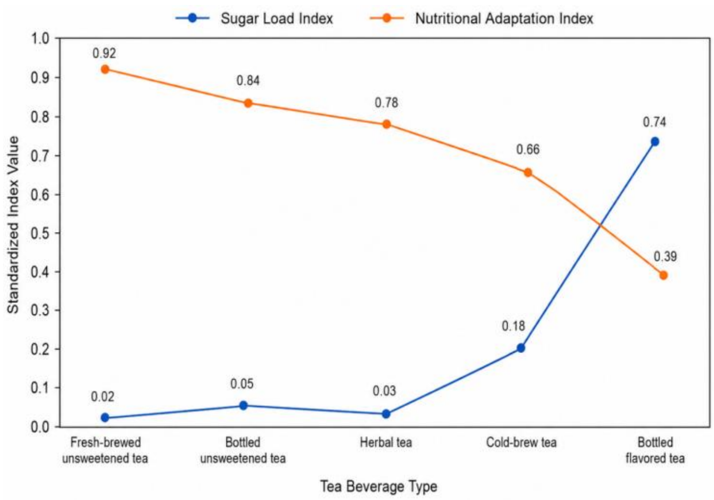

Figure 2. Sugar-load and Nutritional-Adaptation Indices of Different Tea Categories

4.3. Verification of Tea Drinking Risk Classification in People with Special Constitution

The validation of risk classification was carried out around the tolerance threshold and intake context, and the samples of caffeine sensitivity, sleep affected, glucose control need, pregnancy and elderly low tolerance were included in the same framework. Verify the read detection value and overlay drinking period, single volume, weekly frequency, and label sugar content. The results showed that low, medium and high risk of caffeine sensitivity accounted for 28%, 46% and 26%, sleep affected 22%, 41% and 37%, glucose control requirement 18%, 39% and 43%, pregnancy 34%, 45% and 21%, low tolerance 31%, 47% and 22% in the elderly. See Figure 3 for the risk classification results of tea drinking for people with special constitutions.

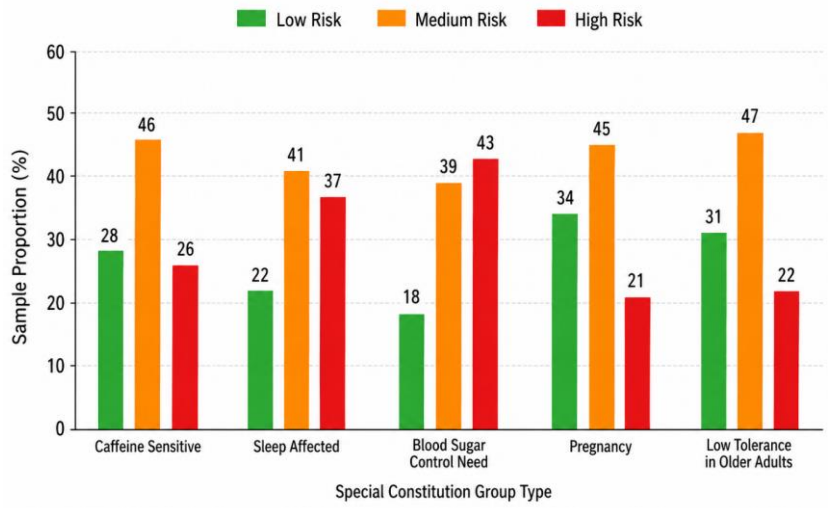

Figure 3. Risk Classification Results of Tea Drinking for People with Special Constitutions

5. Discussion and Nutritional Health Guidance for American Tea Consumers

Age-related differences were not interpreted as direct biological effects but as the combined result of convenience, product exposure, drinking context, and health concern. The preference of respondents aged 18--29 for cold-brewed and ready-to-drink tea may reflect portability, flavor variety, and use in commuting or fitness settings. Greater attention to low-sugar and low-caffeine information among participants aged 45 and above was consistent with the higher relevance of sleep, glucose control, and tolerance in these groups. Sousa et al. found that age significantly influenced tea and herbal-infusion choices and label practices, supporting the age-stratified pattern [3]. USDA beverage data also showed that beverage selection varied across age groups, although the direction of sweetened-beverage change among younger adults was not identical [2]. This difference may arise from product scope and sampling design. Based on these findings, daily drinkers should prioritize fresh-brewed or unsweetened tea, keep a single serving near 200--300 mL, and use label sugar and caffeine information when selecting bottled products. Office users should avoid overlapping strong tea late in the day, while sensitive groups require lower-caffeine options and limits.

6. Conclusion

This study replaced a nominal prediction-model description with a reproducible multi-source analysis path linking 1,200 questionnaires, 36 labels, and 24 tea samples. The results identified age-specific preferences, quantified sugar differences in packaged tea, and reported polyphenol, caffeine, and theanine concentrations with explicit analytical sources. The sugar-load and nutritional-adaptation indices were defined from normalized measured variables, allowing Figure 2 to be recalculated. Fresh-brewed unsweetened tea showed the most favorable balance between active components and sugar control, whereas bottled flavored tea required label-based intake restriction. The findings support differentiated guidance by age, scene, caffeine tolerance, and glucose-control need. Because the study used a limited product and sample set, future work should expand regions, brands, repeated measurements, and prospective follow-up before population-level recommendations are generalized.

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