

Methods and Applications

A Hierarchical Multi-Stage Machine-Learning Study on Predicting Oil and Salt in Chinese Restaurant Dishes for Nutrition Surveillance — 6 Survey Sites, China, 2019–2020

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ABSTRACT

Introduction: The rise in dining out has created a demand for scalable methods for estimating the oil, salt, and sodium content in restaurant meals. These preparation-dependent components are challenging to measure consistently.

Methods: A hierarchical multi-stage prediction model was developed to estimate five dish-level targets: added cooking oil, salt, salt-containing seasonings, sodium from salt-containing seasonings, and total sodium from salt and seasonings in 8,455 Chinese dishes from 192 restaurants across six survey sites in China. The model performance was evaluated using standard regression metrics and task-specific indicators, including zero-use identification, tolerance-based accuracy, multiplicative consistency, symmetric mean absolute percentage error (SMAPE), Spearman's rank correlation, and discrete intake-level classification.

Results: The stage-wise light gradient-boosting machine (LightGBM) model outperformed the linear regression, random forest, and multi-task LightGBM models for all five targets. The log-scale coefficient of determination (R^2) values ranged from 0.224 for salt to 0.570 for salt-containing seasonings. On the original scale, strict tolerance-based accuracy was limited, with 22%–37% of the predictions meeting the tolerance band. Multiplicative and rank-based performances were stronger: 40% to 73% of the predictions were within two-fold of the observed value, and the Spearman correlations ranged from 0.486 to 0.771. The predicted means were lower than the observed means, indicating a conservative estimation and limited suitability for uncalibrated mean estimation.

Conclusion: The model can support the preliminary estimation, relative comparison, and screening of restaurant dishes for nutrition surveillance. Therefore, it should not be interpreted as a precise dish-level measurement tool without further calibration.

Oil, salt, and sodium are key targets for dietary surveillance because their excess intake is associated with obesity, hypertension, and cardiovascular disease (1–3). Surveillance increasingly requires scalable estimates from restaurant dishes; however, direct weighing and laboratory analysis are difficult to scale (4). Existing nutrition estimation methods use food images, labels, recipes, or ingredient data to infer intrinsic nutrients (5–8). The added cooking oil, added salt, and salt-containing seasonings are different; they are preparation-dependent quantities that vary with cooking methods, chef habits, customer requests, recipe standardization, pre-prepared sauces, condiment brands, batch preparation, and kitchen practices. This study developed a hierarchical multistage machine learning framework to evaluate whether routinely collected dish information can support the preliminary estimation and comparison of these targets for nutrition surveillance.

METHODS

Data Sources and Study Targets

Data were obtained from 8,455 restaurant dishes collected during 2019–2020 from 192 restaurants across 6 survey sites selected to cover geographic and culinary diversity: Shijiazhuang, Hebei Province, North China; Xining, Qinghai Province, Northwest China; Daqing, Heilongjiang Province, Northeast China; Changsha, Hunan Province, Central China; Chengdu, Sichuan Province, Southwest China; and Nanchang, Jiangxi Province, East/Southeast China. A total of 2 districts/counties and 32 restaurants were surveyed in each province.

Trained staff collected dish names, ingredients, ingredient weights, cooking methods, and restaurant characteristics through interviews with chefs and on-

site investigations. Identically named dishes from different restaurants were retained as separate records. Five targets were predicted: added cooking oil, salt-containing seasonings, sodium in salt-containing seasonings, salt, and total sodium from added salt and salt-containing seasonings

Data Preprocessing and Feature Description

All targets were log1p-transformed before model fitting, and observations above the 99.5th percentile for each target were excluded. Predictors included three feature blocks: ingredient composition, including total ingredient weight, main ingredient weight, and 65 food-category weight variables; cooking method, including 6 major categories and 22 subtypes; and restaurant-level characteristics, including survey site, north-south region, and restaurant size. The feature definitions are shown in Table 1, and the food category and cooking method classifications are shown in Supplementary Table S1 (available at <https://weekly.chinacdc.cn/>).

Model Development and Design

The primary aim of this study was to predict five dish-level targets: added cooking oil, salt-containing seasonings, sodium in salt-containing seasonings, salt, and total sodium from seasonings and salt. These outcomes are related in both culinary practice and

empirical data, and the pairwise Spearman correlations among them suggested that upstream information could be informative for downstream prediction (Figure 1A). We therefore used a stage-wise framework with five sequential stages (Figure 1B). Stage 1 predicted added cooking oil from the original dish features. Stage 2 predicted salt-containing seasonings using the same features plus the stage 1 output. Stage 3 predicted sodium in salt-containing seasonings using the updated feature set. Stage 4 predicted salt using the original features plus upstream stage outputs. Stage 5 predicted total sodium from seasonings and salt using all previously accumulated stage outputs.

Four models were evaluated to compare different modeling strategies. Linear regression and random forest were implemented as alternative learners using the same stage-wise prediction logic. The multi-task light gradient-boosting machine (LightGBM) model predicted all five targets simultaneously from the same original input features without stage-to-stage feedback. The stage-wise LightGBM model predicted the five targets sequentially and passed predictions forward from one stage to the next.

Model Evaluation and Performance Metrics

Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE) on a

TABLE 1. Feature dictionary for model input variables.

Feature block	Variable name(s)	Definition	Coding	Source/derivation
Ingredient composition	Total ingredient weight	Total recorded weight of the dish	Continuous (g)	Calculated by summing all recorded ingredient weights
	Main ingredient weight	Weight of the dominant ingredient in the dish	Continuous (g)	Calculated from raw ingredient-level records
	65 food-category weight variables	Dish-level total weight assigned to each mapped food category after manual ingredient-to-category mapping	Continuous (g), 0 if absent	Raw item-level ingredients were mapped to the 65-category system and aggregated at the dish level; complete list shown in Table S1
Cooking method	6 major cooking-category indicators	Major cooking category of the dish	Binary indicator (0/1)	Derived from the original coarse cooking-method records and standardized according to the study classification
	22 cooking-subtype indicators	Finer-grained cooking subtype of the dish	Binary indicator (0/1)	Manually refined from original cooking-method information according to the study classification scheme
Restaurant/site level	6 survey-site indicator variables	Survey-site location of the restaurant	Binary indicator (0/1)	Directly derived from recorded restaurant location
	North-south regional indicator	Whether the restaurant was located in southern China	Binary indicator (0/1)	Derived from survey-site location
	Restaurant size indicators	Restaurant scale category (large, medium, small)	Binary indicator (0/1)	Directly recorded in field survey

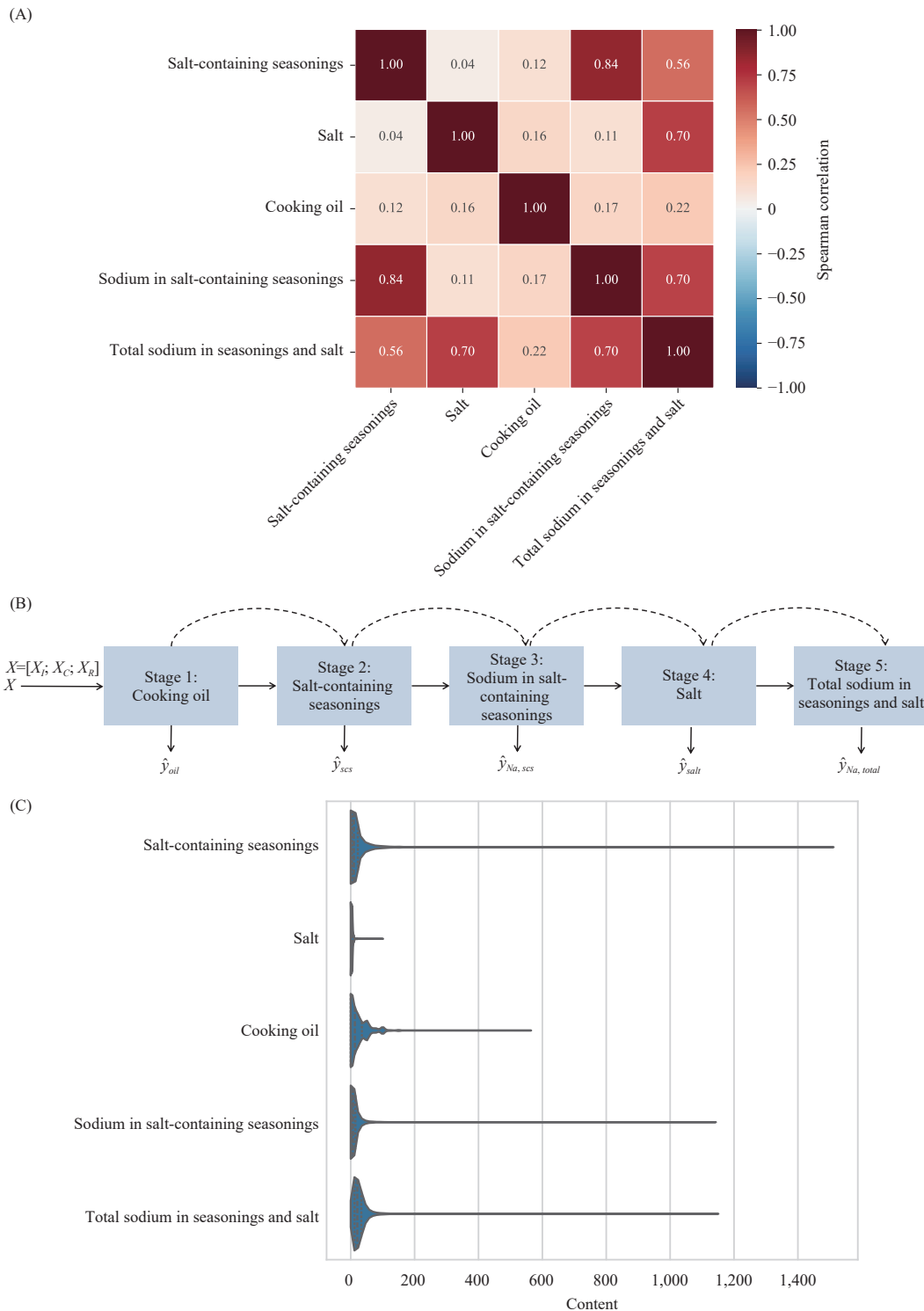


FIGURE 1. Target variable correlations, model framework, and distribution characteristics for predicting oil, salt, and sodium in Chinese restaurant dishes. (A) Spearman correlation heatmap of the five target variables. (B) Hierarchical multi-stage prediction framework. (C) Distribution characteristics of target variables.

Note: For (A), correlations were calculated among added cooking oil, salt-containing seasonings, sodium in salt-containing seasonings, added salt, and total sodium from seasonings and salt. For (B), original dish features from ingredient composition, cooking method, and restaurant/site-level feature blocks were used as initial inputs. The model predicted the five targets sequentially, and each upstream prediction was added to the input of the next stage. Solid arrows indicate forward prediction flow, and dashed arrows indicate out-of-fold predictions used during training to prevent information leakage. For (C), distributions of the five target variables are shown.

log-transformed scale. As the primary goal of this study was to support the rapid estimation of oil, salt, and sodium intake in large-scale nutrition surveillance or surveys, task-specific metrics were also calculated on the original scale, including zero-use identification, tolerance-based accuracy, multiplicative consistency, symmetric mean absolute percentage error (SMAPE), Spearman rank correlation, and discrete intake-level classification. Definitions of these metrics are provided in [Supplementary Table S2](#) (available at <https://weekly.chinacdc.cn/>).

Statistical Analysis

The dataset was split 80/20 into training and test sets. Five-fold cross-validation was applied to the training set. To prevent information leakage, out-of-fold upstream predictions were used as downstream training inputs and the test-set upstream predictions were passed forward during the final evaluation. Subgroup performance was evaluated according to survey site, north-south region, and major cooking-method category. Feature-group contributions were assessed using grouped Shapley additive explanations (SHAP) values for ingredient composition, cooking method, and restaurant-level features.

All analyses were conducted in Python 3.11 using pandas, Numpy, scikit-learn, and LightGBM.

RESULTS

Data Description

The full dataset covered six major cooking categories ([Supplementary Table S1](#)). Mean values per dish were 24.72 g for cooking oil, 21.79 g for salt-containing seasonings, 3.46 g for salt, 1,275.57 mg for sodium in salt-containing seasonings, and 2,663.71 mg for total sodium. The targets were right-skewed and heavy-tailed, consistent with [Figure 1C](#). Of the 8,455 records, 3,729 (44.1%) shared dish names, including 987 repeated dish names. Same-name dishes still varied substantially: median within-name ranges were 27.0 g for cooking oil, 13.5 g for salt-containing seasonings, and 3.0 g for added salt.

Model Results

Statistical metrics on log scale On a log-transformed scale, the stage-wise LightGBM model performed the best for all five targets ([Table 2](#)). The R^2 values were 0.550 for cooking oil, 0.570 for salt-containing seasonings, 0.454 for sodium in salt-containing

seasonings, 0.224 for added salt, and 0.394 for total sodium from seasonings and salt. Subgroup analyses by survey site, north-south region, and major cooking-method category generally supported the stability of the results, although added salt remained the weakest target ([Supplementary Table S3](#), available at <https://weekly.chinacdc.cn/>).

Grouped SHAP analysis showed that ingredient-composition, cooking-method, and restaurant-level features contributed 49.8%, 37.3%, and 12.9% for cooking oil; 52.2%, 37.1%, and 10.7% for salt-containing seasonings; 58.8%, 17.9%, and 23.3% for sodium in salt-containing seasonings; 40.8%, 14.8%, and 44.4% for added salt; and 69.8%, 16.4%, and 13.8% for total sodium, respectively.

Task-specific metrics on original scale The predicted means and standard deviations were lower than the observed values for all five targets ([Table 3](#)), indicating a conservative shrinkage of high values. Thus, raw predictions should be interpreted as preliminary reference values rather than exact dish-level measurements, and calibration is required for absolute mean intake estimation. On the original scale, BandAcc ranged from 0.217 to 0.374, WIF@2× from 0.403 to 0.729, and Spearman's ρ from 0.486 to 0.771, indicating better relative ranking than precise gram-level agreement ([Supplementary Table S2](#)).

DISCUSSION

This study evaluated whether routinely collected restaurant dish information could support the estimation of added oil, salt, salt-containing seasonings, and sodium-related outcomes for nutrition surveillance. Stage-wise LightGBM outperformed the comparison models and showed generally stable performance across survey sites, regions, and cooking-method categories. However, the model should be interpreted as a surveillance support tool for preliminary estimation and comparison, and not as a substitute for direct measurement.

This task differs from conventional nutrient estimation. Intrinsic nutrients can often be estimated from ingredient weights and food composition tables ([5–10](#)), whereas added oil, salt, and salt-containing seasonings depend on preparation practices. Chef habits, customer requests, recipe standardization, pre-prepared sauces, condiment brands, batch preparation, and kitchen practices are difficult to measure consistently. The repeated-dish analysis supports this

TABLE 2. Test-set performance of four regression models*.

Target	Model	R ²	MAE	RMSE
Cooking oil	Linear regression	0.432	0.878	1.226
	Random forest	0.438	0.989	1.225
	LightGBM multi-task	0.527	0.860	1.124
	LightGBM stage-wise (proposed) [†]	0.550	0.831	1.069
Salt-containing seasonings	Linear regression	0.527	0.664	0.870
	Random forest	0.393	0.762	0.994
	LightGBM multi-task	0.544	0.656	0.862
	LightGBM stage-wise (proposed) [†]	0.570	0.632	0.813
Sodium in salt-containing seasonings	Linear regression	0.310	0.662	0.925
	Random forest	0.323	0.727	0.931
	LightGBM multi-task	0.426	0.655	0.858
	LightGBM stage-wise (proposed) [†]	0.454	0.624	0.806
Salt	Linear regression	0.142	0.557	0.711
	Random forest	0.175	0.547	0.704
	LightGBM multi-task	0.165	0.539	0.708
	LightGBM stage-wise (proposed) [†]	0.224	0.518	0.666
Total sodium in seasonings and salt	Linear regression	0.303	0.528	0.746
	Random forest	0.288	0.553	0.790
	LightGBM multi-task	0.327	0.545	0.768
	LightGBM stage-wise (proposed) [†]	0.394	0.506	0.707

Abbreviation: R²=coefficient of determination; MAE=mean absolute error; RMSE=root mean squared error.

* All outcomes were log-transformed.

[†] indicates the primary model used in this study.

TABLE 3. Observed and predicted mean values and standard deviations of the five target variables in the test set.

Target	Observed mean	Observed SD	Predicted mean	Predicted SD	Mean difference (Pred - Obs)
Cooking oil (g)	24.84	34.84	17.13	20.18	-7.70
Salt-containing seasonings (g)	21.63	41.35	14.31	16.01	-7.32
Sodium in salt-containing seasonings (mg)	1,301.05	2,487.01	888.15	886.21	-412.90
Salt (g)	3.55	4.59	2.65	1.35	-0.89
Total sodium in seasonings and salt (mg)	2,745.68	3,633.57	2,162.92	1,267.24	-582.75

Abbreviation: SD=standard deviation; Pred=predicted; Obs=observed.

point: identical dish names do not necessarily represent standardized recipes or stable seasoning amounts.

The feature-contribution results also support the use of multiple information sources. Ingredient composition captured much of the dish-level structure, cooking methods captured preparation-related variation, and restaurant-level variables captured part of geographic or operational variation, especially for added salt. Restaurant size was included as a predictor; however, it is only a coarse indicator and cannot

directly measure recipe standardization or chef-level practices.

The model's public health value lies in its screening and prioritization. In large-scale monitoring, direct measurement of restaurant dishes is often impractical. Approximate model outputs can help field investigators identify dishes, cooking methods, regions, or restaurant types that are likely to have high oil or sodium content and prioritize them for further assessment or intervention. Raw predictions should not be used for

menu labeling, regulatory enforcement, individual dietary assessment, or uncalibrated estimation of the population mean intake.

The findings in this report are subject to some limitations. First, although the dataset covers diverse survey sites, it was not designed to generate province-specific estimates. Second, the target values derived from chef interviews and on-site investigations may contain measurement errors. Third, routinely collected predictors did not include condiment brands, chef-specific habits, customer requests, or detailed cooking process information. Fourth, external validation and calibration are required before broader application.

In conclusion, routinely collected dish information can support the preliminary estimation and relative comparison of oil, salt, and sodium in Chinese restaurant dishes, while revealing clear limits for precise gram-level prediction.

Conflicts of interest: No conflicts of interest.

Funding: Supported by Public Health Emergency Project Nutrition Health and Healthy Diet Campaign (No. 102393220020070000012).

doi: [10.46234/ccdcw2026.184](https://doi.org/10.46234/ccdcw2026.184)

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Submitted: January 27, 2026

Accepted: May 22, 2026

Issued: September 04, 2026

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SUPPLEMENTARY MATERIAL

SUPPLEMENTARY TABLE S1. Food-category mapping and hierarchical cooking-method classification used in feature construction.

Classification domain	Category	Subcategories	Frequency in the dataset (n)*
Cooking categories	Cold dishes and cold mixed noodles	Light cold dish type, Heavily sauced cold dish type, Spicy and oily cold dish type, Oily cold dish type, Mildly seasoned staple dish type, Mildly seasoned cold dish type	1,539
	Braised, marinated, and sugar-based preparations	Traditional braised type, Composite sauce-braised type, Grilled and sauced braised type	407
	Steamed and boiled dishes	Plain steamed type, Sauced steamed type	662
	High-heat stir-frying	Home-style stir-fried type, Dry-pot stir-fried type, Sauce-rich stir-fried type, Spicy stir-fried type	3,353
	Moist-heat cooking	Clear-soup braised type, Richly seasoned braised type, Hotpot base-braised type, Heavy-oil braised type	1,689
	Deep-fried, pan-fried, and grilled/roasted dishes	Plain-fried or grilled type, Marinated fried or grilled type, Sauced fried or grilled type	805
Food categories	Eggs and egg products	Quail eggs, goose eggs, chicken eggs, duck eggs	610
	Beverages	Popsicles and ice cream, tea and tea beverages, powdered beverages, fruit juices and fruit drinks, milk beverages, carbonated beverages, plant-protein beverages	69
	Fish, shrimp, crab and shellfish	Shellfish, shrimp, crab, fish	1,173
	Dried legumes and legume products	Broad beans, adzuki beans, soybeans, mung beans, kidney beans	770
	Vegetables and vegetable products	Allium vegetables, root vegetables, tender-stem-leafy and flowering vegetables, fruiting and gourd vegetables, aquatic vegetables, fresh legumes, wild vegetables	14,473
	Cereals and cereal products	Barley, rice, wheat, millet and yellow millet, corn	576
	Snacks and sweet baked goods	Cakes and desserts, snacks	93
	Tubers, starches and related products	Starches	985
	Fats and oils (excluding added cooking oil)	Animal fats	362
	Poultry and poultry products	Goose meat, chicken, duck	666
	Alcoholic beverages	Fermented alcoholic beverages, distilled spirits	117
	Sugars, preserved fruits, candied fruits and honey	Honey, preserved and candied fruits, candy	74
	Fruits and fruit products	Citrus fruits, melons and stone fruits, berries, tropical and subtropical fruits, pome fruits	231
	Livestock meat and meat products	Donkey meat, beef, lamb and mutton, pork	3,790
	Milk and dairy products	Milk powder, cheese, cream, yogurt, liquid milk	28
	Nuts and seeds	Tree nuts, seeds	445
	Condiments and seasonings (seasonings not included in this study)	Pickled vegetables, herbs and spices	1,751

* For cooking categories, *n* denotes the number of dishes assigned to that category; for food categories, *n* denotes the number of occurrences of that category across dishes.

Interpretation of Task-Specific Performance Metrics in Supplementary Table S2

The task-specific metrics in Supplementary Table S2 were used to complement the standard log-scale regression metrics by evaluating model performance on the original scale. These metrics were intended to assess whether the predictions could support preliminary estimation, relative comparison, and screening in nutrition surveillance rather

SUPPLEMENTARY TABLE S2. Task-specific performance metrics of the stage-wise LightGBM model*.

Target	ZeroAcc@0.1	ZeroPrec@0.1	ZeroRec@0.1	ZeroF1@0.1	BandAcc@abs 0.5+20%†	EpsMAE@abs 0.5+20%†	WIF@1.5×	WIF@2×	SMAPE	Spearman ρ	ClsAcc (bins)	MacroF1 (bins)
Cooking oil	0.086	0.867	0.086	0.157	0.217	8.141	0.285	0.403	1.010	0.767	0.286	0.254
Salt- containing seasonings	0.021	1.000	0.021	0.041	0.258	6.596	0.370	0.555	0.739	0.771	0.350	0.257
Sodium in salt- containing seasonings	0.040	1.000	0.040	0.077	0.279	3.666	0.350	0.539	0.770	0.667	0.325	0.253
Salt	0.016	0.750	0.016	0.031	0.374	0.893	0.366	0.547	0.841	0.486	0.412	0.241
Total sodium in seasonings and salt	0.034	1.000	0.034	0.067	0.324	5.591	0.508	0.729	0.517	0.595	0.469	0.239

Abbreviation: ZeroAcc@0.1=zero-use accuracy at threshold 0.1; ZeroPrec@0.1=zero-use precision at threshold 0.1; ZeroRec@0.1=zero-use recall at threshold 0.1; ZeroF1@0.1=zero-use F1 score at threshold 0.1; BandAcc=tolerance-based band accuracy; EpsMAE=epsilon mean absolute error beyond tolerance band; WIF=within interval factor; SMAPE=symmetric mean absolute percentage error; ClsAcc=classification accuracy; MacroF1=macro F1 score.

* All metrics were calculated using the original scale. The values for cooking oil, salt-containing seasonings, and added salt are in grams, and sodium-related quantities are in milligrams, except for dimensionless metrics.

† For the abs0.5+20% criterion, the average tolerance bands on the original scale were 5.44 g for salt-containing seasonings, 305 mg for sodium in salt-containing seasonings, 1.19 g for added salt, and 583 mg for total sodium in seasonings and salt. The EpsMAE reports the mean excess absolute error beyond this band.

SUPPLEMENTARY TABLE S3. Subgroup performance of the stage-wise LightGBM model by survey site, cooking method, and north-south region.

Subgroup	Category	n	Target	R ² *	MAE*	RMSE*	Spearman's ρ
site	Shijiazhuang	258	Cooking oil (g)	0.490	0.766	0.975	0.743
			Salt-containing seasonings (g)	0.584	0.630	0.816	0.778
			Sodium from salt-containing seasonings (mg)	0.428	0.682	0.848	0.616
			Salt (g)	0.128	0.438	0.586	0.319
	Xining	282	Total sodium in seasonings and salt (mg)	0.471	0.450	0.591	0.548
			Cooking oil (g)	0.386	0.939	1.141	0.555
			Salt-containing seasonings (g)	0.496	0.574	0.765	0.727
			Sodium in salt-containing seasonings (mg)	0.357	0.621	0.817	0.559
	Nanchang	277	Salt (g)	0.081	0.617	0.782	0.274
			Total sodium in seasonings and salt (mg)	0.323	0.655	0.880	0.456
			Cooking oil (g)	0.465	0.805	1.063	0.765
			Salt-containing seasonings (g)	0.446	0.616	0.853	0.709
	Chengdu	300	Sodium in salt-containing seasonings (mg)	0.412	0.544	0.765	0.643
			Salt (g)	0.033	0.356	0.543	0.135
			Total sodium in seasonings and salt (mg)	0.177	0.336	0.528	0.573
			Cooking oil (g)	0.519	1.040	1.303	0.680
	Daqing	294	Salt-containing seasonings (g)	0.523	0.664	0.872	0.709
			Sodium in salt-containing seasonings (mg)	0.351	0.683	0.900	0.562
			Salt (g)	0.078	0.663	0.792	0.335
			Total sodium in seasonings and salt (mg)	0.253	0.661	0.901	0.461
	Changsha	280	Cooking oil (g)	0.523	0.828	1.087	0.739
			Salt-containing seasonings (g)	0.623	0.650	0.825	0.798
			Sodium in salt-containing seasonings (mg)	0.510	0.632	0.822	0.705
			Salt (g)	0.160	0.562	0.717	0.435
Region	North	834	Total sodium in seasonings and salt (mg)	0.380	0.511	0.739	0.594
			Cooking oil (g)	0.491	0.815	1.068	0.738
			Salt-containing seasonings (g)	0.473	0.784	0.986	0.678
			Sodium in salt-containing seasonings (mg)	0.368	0.754	0.938	0.604
	South	857	Salt (g)	0.101	0.479	0.633	0.369
			Total sodium in seasonings and salt (mg)	0.321	0.509	0.720	0.588
			Cooking oil (g)	0.541	0.846	1.073	0.757
			Salt-containing seasonings (g)	0.584	0.618	0.803	0.780
			Sodium in salt-containing seasonings (mg)	0.441	0.644	0.829	0.640
			Salt (g)	0.146	0.542	0.703	0.385
			Total sodium in seasonings and salt (mg)	0.387	0.541	0.750	0.546

Continued

Subgroup	Category	n	Target	R ² *	MAE*	RMSE*	Spearman's ρ
Cooking method	High-heat stir-frying	689	Cooking oil (g)	0.554	0.792	1.003	0.821
			Salt-containing seasonings (g)	0.485	0.657	0.860	0.709
			Sodium in salt-containing seasonings (mg)	0.400	0.638	0.821	0.603
			Salt (g)	0.243	0.466	0.631	0.518
	Moist-heat cooking	328	Total sodium in seasonings and salt (mg)	0.307	0.464	0.658	0.567
			Cooking oil (g)	0.504	0.892	1.166	0.710
			Salt-containing seasonings (g)	0.655	0.517	0.706	0.857
			Sodium in salt-containing seasonings (mg)	0.525	0.523	0.722	0.743
	Cold dishes and cold mixed noodles	292	Salt (g)	0.199	0.529	0.690	0.490
			Total sodium in seasonings and salt (mg)	0.255	0.472	0.665	0.558
			Cooking oil (g)	0.582	0.780	0.984	0.672
			Salt-containing seasonings (g)	0.475	0.735	0.974	0.695
	Deep-Fried, Pan-Fried, and Grilled/Roasted Dishes	148	Sodium in salt-containing seasonings (mg)	0.325	0.732	0.959	0.563
			Salt (g)	0.200	0.556	0.732	0.479
			Total sodium in seasonings and salt (mg)	0.421	0.610	0.873	0.543
			Cooking oil (g)	0.245	1.079	1.435	0.567
	Steamed and Boiled Dishes	140	Salt-containing seasonings (g)	0.617	0.741	0.899	0.802
			Sodium in salt-containing seasonings (mg)	0.495	0.742	0.916	0.718
			Salt (g)	0.215	0.598	0.740	0.503
			Total sodium in seasonings and salt (mg)	0.422	0.659	0.889	0.609
	Braised, Marinated, and Sugar-Based Preparations	94	Cooking oil (g)	0.185	1.036	1.307	0.455
			Salt-containing seasonings (g)	0.622	0.655	0.810	0.789
			Sodium in salt-containing seasonings (mg)	0.499	0.622	0.803	0.706
			Salt (g)	0.058	0.558	0.701	0.346
			Total sodium in seasonings and salt (mg)	0.271	0.554	0.742	0.581
			Cooking oil (g)	0.502	1.043	1.202	0.733
			Salt-containing seasonings (g)	0.485	0.713	0.907	0.680
			Sodium in salt-containing seasonings (mg)	0.302	0.868	1.057	0.515
			Salt (g)	0.217	0.641	0.781	0.498
			Total sodium in seasonings and salt (mg)	0.352	0.609	0.894	0.604

Abbreviation: R²=coefficient of determination; MAE=mean absolute error; RMSE=root mean squared error; ρ =Spearman's rank correlation coefficient.

* All outcomes are on the log-transformed scale.

than to claim precise dish-level measurements.

Zero-use detection (ZeroAcc, ZeroPrec, ZeroRec, ZeroF1). Zero-use metrics evaluate whether the model correctly identifies dishes with negligible or no use of the target ingredient or seasoning. Across the five targets, zero-use recall was low, but precision was high, indicating that the model rarely predicted exact zero values; however, when it did, such predictions were usually correct. This suggests that the model tends to assign small positive values, rather than strictly zero values. Therefore, predictions should not be used as definitive indicators of nonuse.

Tolerance-based accuracy (BandAcc and EpsMAE). BandAcc was calculated using a strict tolerance band defined as absolute error ≤ 0.5 plus 20% of the true value on the original scale. The BandAcc ranged from 0.217 to 0.374 across the targets, indicating limited agreement under this strict criterion. The EpsMAE further quantified the

average excess error beyond the tolerance band. These results show that precise gram- or milligram-level prediction remains difficult, especially for dishes with large variabilities in oil, salt, or seasoning use.

Multiplicative agreement and ranking (WIF@1.5×/WIF@2× and Spearman's ρ). WIF@1.5× and WIF@2× assessed whether the predicted values remained within a specified multiplicative range of the observed values. Spearman's ρ assessed whether the model preserved rank ordering across dishes. Compared with strict tolerance-based accuracy, multiplicative and rank-based performance was stronger, with WIF@2× ranging from 0.403 to 0.729 and Spearman's ρ ranging from 0.486 to 0.771. These findings indicate that the model captured broad relative differences and approximated magnitudes better than the exact dish-level amounts.

Bin-based classification metrics (ClsAcc and MacroF1). ClsAcc and MacroF1 were used to evaluate whether the predicted and observed values fell within the same predefined intake categories. The moderate classification results suggest that the model partly preserved the intake level categories, but the category agreement was not sufficient for the precise classification of individual dishes.

Overall interpretation. Taken together, these metrics indicate that the model provides useful preliminary reference estimates for nutrition surveillance, particularly for comparing dishes and identifying those likely to have relatively high oil, salt, or sodium content. However, this model should not be interpreted as a substitute for direct weighing, recipe dissection, or laboratory analysis. Raw predictions are more appropriate for surveillance-oriented screening and prioritization than for precise dish-level gram measurements or uncalibrated estimations of absolute mean intake.