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FoodByte: a personalized food scoring and additive risk assessment algorithm for smarter eating

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Abstract
Current front-of-package food-scoring systems, such as Nutri-Score, summarize nutritional quality using population-level criteria but do not account for individual health conditions, food additives, or allergen sensitivities. We developed FoodByte, a rule-based personalized food-scoring framework integrating nutrient composition, literature-informed additive-risk heuristics, allergen detection, and disease-specific scoring rules to generate individualized food ratings. FoodByte was evaluated using 50 commercially available packaged foods across five representative health profiles (250 product-profile evaluations) and compared with Nutri-Score. Differences between scoring systems were analyzed using descriptive statistics and a cross-classified linear mixed-effects model with random intercepts for food product and health profile. Sensitivity analyses and model diagnostics assessed score divergence and algorithmic robustness. FoodByte produced systematically lower scores than Nutri-Score for many processed foods, with an estimated mean difference of −10.49 points (95% CI: −14.50 to −6.48, $p = 2.88 \times 10^{-7}$). Disease-specific profiles showed larger score divergence than the control profile, with mean percentage differences ranging from 24.4% to 41.6%, compared with 11.6% for controls. Variance-component analysis indicated that intrinsic nutritional characteristics established the primary baseline for food evaluation, while disease-specific personalization selectively modified recommendations for foods containing condition-relevant nutrients or additives and preserved consistent recommendations for foods broadly suitable across health profiles. Sensitivity analyses demonstrated high internal stability across algorithmic perturbations, with correlations generally exceeding 0.98. These findings demonstrate that additive-aware, disease-specific scoring can systematically modify a population-level nutrient-profiling framework while remaining internally robust. Rather than uniformly re-ranking foods, FoodByte selectively personalizes recommendations where disease-specific nutritional considerations are most relevant. Because the products were purposively selected and no clinical outcomes were evaluated, the findings should be interpreted as evidence of algorithmic divergence and internal robustness rather than clinical superiority. Future studies should validate personalized food-scoring systems against clinical outcomes, expert assessments, and consumer decision-making.

Keywords
Personalized nutrition, Food scoring algorithm, Nutrient profiling, Food additives, Nutrition informatics, Dietary assessment, Precision nutrition, Food labeling, Digital health, Public health nutrition

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1. Introduction

Ultra-processed foods comprised 57.9% of total energy intake in the American diet, representing nearly three in five calories, based on nationally representative U.S. data from 2009–2010 (1) frequently contain additives that have been linked to chronic diseases and adverse health outcomes, including cancer (2), metabolic dysfunction, and obesity-related inflammatory disorders (3). Despite regulatory approval by the FDA, many additives permitted in the U.S. are increasingly linked to significant safety concerns, including endocrine disruption (4) and the breakdown of intestinal barriers that may trigger autoimmune diseases (5). For instance, potassium bromate, a dough conditioner linked to carcinogenic effects, remains legal in U.S. food products but is banned in the European Union, Canada, and numerous other countries (6, 7).

Current food-scoring systems attempt to provide consumers with simplified nutritional guidance to support healthier dietary choices. The most prominent system, Nutri-Score, developed in France and adopted across Europe, uses an A—E grading system based on nutritional content per 100 grams, including energy density, sugar, saturated fat, sodium, fiber, protein, and fruit, vegetable, or nut content (8). While Nutri-Score is not currently implemented in the United States, it serves as a representative example of population-level nutritional scoring systems and provides a validated benchmark for comparative analysis, as its methodology is publicly available and widely studied. While useful for quick comparisons within product categories, these systems exhibit several critical limitations that undermine their effectiveness for diverse consumer populations.

First, population-level scoring approaches fail to account for individual health conditions or goals. A product rated favorably for the general population may be inappropriate for individuals with diabetes, hypertension, or other metabolic conditions. Second, current systems provide minimal consideration of potentially harmful food additives despite growing scientific evidence of health risks associated with preservatives and artificial sweeteners (2), as well as emulsifiers, which emerging mechanistic studies increasingly associate with gut microbiome disruption and metabolic dysfunction (9, 10). Third, allergen handling remains rudimentary, with limited integration of personalized allergen warnings beyond basic declarations. Fourth, these systems lack contextual explanations that would help consumers understand why a product received a particular score and what specific ingredients or nutritional factors contributed to the rating.

Peters and Verhagen (2022) evaluated the Nutri-Score system using European Food Safety Authority (EFSA) criteria and identified significant gaps in its scientific substantiation, concluding that there is insufficient evidence to prove the label creates a measurable benefit to human health (8). Romero Ferreiro et al. (2021) emphasize that evaluating food health requires considering both nutritional quality and degree of processing, as single-dimension scoring systems like Nutri-Score fail to capture the full health impact of a product (11). These critiques highlight a limitation in current food evaluation methodologies: the need for comprehensive, personalized assessment tools that integrate nutritional quality, additive safety, and individual health considerations.

The vast number of chemical substances in the American food supply, exceeding 14,000 intentional and unintentional additives, raises significant questions regarding long-term public health. While the National Research Council has established clear links between certain food components and carcinogenesis, the FDA's regulatory framework often struggles to quantify the exact magnitude of risk these substances pose to human populations (2). Subsequent research has linked specific additives to hyperactivity in children (12, 13), respiratory issues in individuals with asthma (14), endocrine disruption (15), potential carcinogenicity (6), and cellular-level neurotoxic effects in the brain (16). Despite this evidence, regulatory action remains limited, leaving consumers vulnerable to cumulative exposure effects from multiple additives across their diet.

Beyond Nutri-Score, consumer-facing apps like Yuka have gained widespread popularity but face serious scientific credibility issues from nutrition experts. Registered dietitian Kacie Barnes criticizes the Yuka app's scoring system as overly simplistic and inconsistent, arguing that its approach to ranking additives and ingredient effects does not reliably reflect their actual risk or nutritional relevance (17). Additionally, Yuka awards a 10% score bonus to organic products despite limited evidence of consistent nutritional superiority (18, 19), and does not account for individual health needs, assigning the same product scores to all users regardless of dietary context or medical status (20). These limitations underscore the need for evidence-based, personalized alternatives.

Developing personalized food-scoring frameworks may help explore how food evaluation changes when individual health profiles, additive-related concerns, and allergen information are incorporated. This study introduces FoodByte, a rule-based food-scoring prototype designed to compare a population-level nutrient-profiling baseline with additive-aware and profile-specific scoring rules. The goal of this study is to evaluate score divergence and internal robustness within a defined sample, not to establish clinical efficacy or population-level health impact.

The primary research question addressed by this study is: *How can a rule-based food-scoring algorithm be designed to incorporate nutritional quality, additive-risk flags, and individual health-profile rules, and how do its resulting scores differ from a population-level nutrient-profiling baseline in a defined sample?*

This study hypothesizes that a personalized food-scoring algorithm integrating additive-risk flags and health-profile-specific scoring rules will produce average score differences of at least 20% compared with a population-level nutrient-profiling baseline across the evaluated product–profile combinations. This hypothesis tests whether the scoring frameworks diverge meaningfully in this sample; it does not test clinical superiority or health outcome prediction.

2. Materials and Methods

2.1 Algorithm development

2.1.1 *Overview of the FoodByte scoring framework*

FoodByte is a personalized food evaluation system that integrates nutrient composition, food additive risk profiling, and user-specific

health factors to generate an interpretable 0–100 health score for packaged foods. The system leverages publicly available nutritional data from Open Food Facts and applies rule-based, evidence-informed adjustments derived from clinical nutrition guidelines. The final score represents a composite measure of nutritional quality, adjusted for individual health conditions, dietary goals, and sensitivity to specific ingredients.

2.1.2 *Data acquisition and preprocessing*

Food product data were retrieved through the Open Food Facts API using barcode identifiers. The extracted information included nutrient content per 100 g, specifically energy, total fat, saturated fat, sugar, sodium, protein, and fiber; the free-text ingredient list; and the Nutri-Score grade and numeric score when these values were available. Ingredient text was normalized to lowercase and processed through keyword-based matching to identify additives, allergens, and relevant ingredient categories.

2.1.3 *Base nutritional scoring*

FoodByte uses the official Nutri-Score value provided by Open Food Facts as its baseline nutritional indicator. This score is derived from the Food Standards Agency modified Nutrient Profiling System (FSAm-NPS), which assigns penalty and reward points based on nutrient density. The Nutri-Score was treated as an externally validated input rather than recomputed internally. When available, the system extracted both the raw Nutri-Score value and its corresponding letter grade from A to E. The Nutri-Score was then normalized to a 0–100 scale using the transformation applied to the API-provided value. When Nutri-Score information was unavailable, a neutral default value was applied. This design ensured alignment with the official Nutri-Score methodology while enabling downstream personalization.

2.1.4 *Additive risk scoring system*

A comprehensive database of 60+ food additives was developed with risk scores assigned on a 1–10 scale based on documented health impacts, regulatory status, and strength of scientific evidence. Ingredient lists were scanned for known additive names and aliases. When a match was found, the corresponding base risk score is applied. Additives were grouped into the functional categories of preservatives, artificial colors, sweeteners, emulsifiers and thickeners, flavor enhancers, contaminants and processing byproducts, and phosphates and sulfites. Certain health conditions were treated as increasing sensitivity to particular additive classes.

Accordingly, sulfite-related risk was increased for individuals with asthma, artificial-color risk was increased for individuals with ADHD, added-sugar and sweetener risk was increased for individuals with diabetes, phosphate-additive risk was increased for individuals with chronic kidney disease, and trans-fat and saturated-fat risk was increased for individuals with cardiovascular disease.

Food additives were assigned expert-defined, rule-based heuristic risk scores on an ordinal 1–10 scale. These scores were informed by published toxicological, epidemiological, regulatory, and clinical evidence, but they were not empirically estimated from clinical outcome data, exposure-response modeling, or population-level validation. Accordingly, the scores represent relative risk indicators within the FoodByte scoring framework and should not

be interpreted as quantitative estimates of toxicity, absolute health risk, or dose-response relationships.

Risk assignments were informed by regulatory actions, epidemiological studies, toxicological evidence, and consensus reports from agencies such as the FDA, EFSA, IARC, and WHO. The purpose of this heuristic scoring system was to support transparent, interpretable comparison of additive-related concerns within the FoodByte framework, not to estimate absolute health risk or replace formal toxicological risk assessment.

2.1.4.1 Risk scoring criteria

Risk Score 9–10 (Extreme Risk): Additives banned in multiple countries due to strong evidence of toxicity or carcinogenicity. Examples include potassium bromate [10], acrylamide [10], trans fats [10], and perfluoroalkyl substances (PFAS) [10].

Risk Score 7–8 (Serious Risk): Possible carcinogens with DNA damage potential, or substances causing significant endocrine disruption or neurological effects. Examples include butylated hydroxyanisole (BHA) [8], titanium dioxide [8], aspartame [8], and propylparaben [8].

Risk Score 5–6 (Moderate Risk): Substances associated with metabolic or neurological effects, known to trigger allergies, hyperactivity, or digestive distress. Examples include monosodium glutamate (MSG) [6], sodium benzoate [6], Yellow 5/tartrazine [6], and propylene glycol alginate [6].

Risk Score 3–4 (Slight Concern): Mild effects in sensitive individuals or substances with inconclusive but suggestive evidence. Examples include sorbic acid [4], modified food starch [4], xanthan gum [3], and cellulose gum [3].

Risk Score 1–2 (Minimal Risk): No strong evidence of harm at typical consumption levels.

2.1.4.2 Scientific justification for key additives

Potassium Bromate (Score 10): Potassium bromate, a dough conditioner linked to carcinogenic effects in animal studies, remains legal in U.S. food products but has been banned in the European Union, Canada, and several other countries including the United Kingdom, Nigeria, Sri Lanka, Brazil, Colombia, China, India, Australia, and New Zealand (6, 7).

Aspartame (Score 8): Aspartame was classified as possibly carcinogenic to humans by the International Agency for Research on Cancer in 2023 (21), and the American Diabetes Association 2025 guidelines recommend that nonnutritive sweeteners be consumed in moderation and for the short term (22).

BHA (Butylated Hydroxyanisole) (Score 8): Preservative shown to be carcinogenic in animal studies with evidence of tumor formation in laboratory rodents (23).

Artificial Colors - Red 40 (Score 7), Yellow 5 (Score 6), Yellow 6 (Score 7): Linked to hyperactivity in children. McCann et al. (2007) found significant increases in hyperactivity with artificial colors plus sodium benzoate in children (12). The European Union requires warning labels on products containing these additives.

Titanium Dioxide (Score 8): Emulsifier and whitening agent banned in the EU as of 2022 due to concerns about potential DNA damage and genotoxicity (24).

Sodium Benzoate (Score 6): Forms benzene, a known carcinogen, when combined with ascorbic acid (vitamin C) under certain conditions (25).

Sulfites (Score 7, elevated to 20 for asthma patients): Widely used as preservatives and

antioxidants, and can trigger severe respiratory reactions, including bronchospasm, in sensitive individuals. Among asthmatics, approximately 3–10% exhibit sulfite sensitivity, with some experiencing life-threatening responses (14).
MSG (Monosodium Glutamate) (Score 6): Flavor enhancer that may elicit headaches or other neurological symptoms in a small subset of individuals at high doses (>2.5 g) when consumed without food, though responses are generally inconsistent (26).

The complete additive risk scoring database with full justifications and citations is provided in Supplementary Document S1. The total additive penalty was computed as the sum of all detected additive risk scores and was capped at 50% of the base nutritional score to prevent over-penalization. This penalty was integrated into the personalized scoring calculation with disease-specific modifications.

2.1.5 *Personalization parameters with literature-informed rule-based thresholds*
FoodByte incorporates individualized adjustments based on health profile information including diseases, health goals, activity levels, and daily caloric intake. Thresholds and adjustments were informed by clinical guidelines and peer-reviewed literature where available. Some per-100 g cutoffs are pragmatic operationalizations of broader dietary guidance rather than directly validated clinical thresholds.

2.1.5.1 Disease-based adjustments
The American Diabetes Association 2025 Standards of Care emphasize minimizing added sugars and refined grains while supporting a daily fiber intake of approximately 25–30 g (27, 28). Within FoodByte, products containing more than 5 g of sugar per 100 g were assigned a penalty of 2 points for each gram above the threshold, capped at 15 points. Products containing more than 3 g of fiber per 100 g were assigned a reward of 2 points for each gram above the threshold, capped at 10 points. The presence of refined grains among the first three ingredients resulted in a 5-point penalty, while protein content above 10 g per 100 g was assigned a reward of 1 point for each gram above the threshold, capped at 5 points. High-fructose corn syrup and sweeteners were also assigned condition-specific additive-risk increases of 5 and 3 points, respectively.

The Dietary Approaches to Stop Hypertension, or DASH, dietary pattern emphasizes fruits, vegetables, and low-fat dairy products while reducing saturated-fat consumption. When combined with low sodium intake of ~ 1,500 mg per day, this pattern reduced systolic blood pressure by ~ 7–11 mmHg in adults with hypertension, with similar reductions observed among men, women, and Black and non-Black participants (29, 30). For FoodByte, sodium concentrations above 0.23 g per 100 g were assigned a penalty of 15 points for each additional 0.1 g, capped at 30 points. Sodium concentrations between 0.15 and 0.23 g per 100 g were assigned a penalty of 10 points for each additional 0.1 g, capped at 20 points. Products containing more than 5 g of saturated fat per 100 g were assigned an additional 5-point penalty, while the presence of processed meat was assigned a 10-point penalty. Sodium-containing additives, such as monosodium glutamate, were assigned an additional additive-risk increase of three points.

AHA/ACC guidelines recommend Mediterranean-style or “provegetarian” dietary patterns that emphasize plant-based proteins,

nuts, and vegetable fibers. These dietary patterns are clinically associated with a lower risk of all-cause mortality than standard diets, and the landmark PREDIMED trial demonstrated an ~ 30% reduction in major cardiovascular events (31). For FoodByte, the presence of trans fats or partially hydrogenated oils resulted in an assigned 25-point penalty. Saturated-fat concentrations between 5 and 10 g per 100 g produced an assigned 8-point penalty, while concentrations above 10 g per 100 g resulted in an assigned 15-point penalty. Fiber concentrations above 3 g per 100 g generated an assigned reward of 3 points for each gram above the threshold, capped at 12 points.

The KDIGO 2024 Clinical Practice Guideline recommends limiting dietary sodium intake to less than 2,000 mg per day among individuals with chronic kidney disease and emphasizes reducing foods containing phosphate additives because of their high bioavailability and contribution to phosphorus burden (32). FoodByte therefore increased the assigned additive-risk contribution of phosphate-containing additives by 20 points. Sodium concentrations above 0.2 g per 100 g resulted in an assigned penalty calculated as [−60 × (sodium − 0.2)], capped at a maximum 12-point deduction.

The low-FODMAP diet developed by Monash University has been shown to significantly reduce gastrointestinal symptoms among patients with irritable bowel syndrome. In a randomized, controlled, single-blind crossover trial, approximately 70% of patients with IBS experienced a clinically meaningful improvement in overall symptoms while consuming a low-FODMAP diet compared with a typical diet (33). For FoodByte, the presence of sorbitol, mannitol, or xylitol resulted in an assigned additive-risk value of 12 points. High-fructose corn syrup resulted in an assigned 8-point penalty, and total fat concentrations above 15 g per 100 g resulted in an assigned 6-point penalty.

Lactose malabsorption, which is a necessary underlying condition for lactose intolerance, affects ~ 68% of the global population, although not all individuals with malabsorption develop symptomatic lactose intolerance (34). Under the FoodByte rule set, the presence of milk or lactose resulted in an assigned 15-point penalty, the presence of whey, in an assigned 12-point penalty, and the presence of cheese, butter, or cream, in an assigned 8-point penalty.

Because sulfites can trigger severe respiratory reactions in ~ 3–10% of individuals with asthma (14), the additive-risk contribution for sulfites was increased to 20 points when sulfites were detected in a product evaluated under the asthma profile.

2.1.5.2 Health goal adjustments

For users pursuing weight loss, a calorie-density penalty was assigned when a product contained more than 150 kcal per 100 g. The adjustment was calculated as, $calorie\ penalty = -\frac{(calories - 150)}{50}$ (eq1). For users pursuing muscle gain, a protein reward was assigned when protein content exceeded 5 g per 100 g. The adjustment was calculated as, $protein\ reward = +(protein - 5)$ (eq2).

2.1.5.3 Activity level adjustments

For users with a high activity level, products containing more than 10 g of protein per 100 g

received an additional assigned 5 points to reflect increased protein requirements. For users who identified hydration as a priority, products were assigned an additional 3 points when water or ingredients with high water content, including fruits and vegetables, were present. These modifiers reflect practical dietary optimization rather than medical diagnosis.

2.1.6 *Final score computation*

The final personalized score integrated all components as shown by eq3. They were also constrained to the 1-100 range as shown in eq4.

$$\text{personalized score} = \text{base score} - \text{additive penalty} + \text{personalized adjustments} \quad \text{(eq3)}$$

$$\text{final score} = \max(1, \min(100, \text{personalized score})) \quad \text{(eq4)}$$

2.2 Data collection

2.2.1 *Product selection*

Fifty commercial food products were selected to represent diverse categories commonly consumed in the American diet. Products were distributed across six categories: snacks (n=23), beverages (n=5), breakfast items (n=5), condiments (n=5), dairy products (n=7), and grains (n=5). Product selection aimed to include a range of nutritional profiles from minimally processed products to ultra-processed products to ensure adequate variance for comparative analysis. Because products were purposively selected to represent nutritional diversity rather than randomly sampled, the selection process could introduce selection bias. Future studies should employ stratified random sampling within product categories.

Nutritional data for all products were obtained from the Open Food Facts API (https://world.openfoodfacts.org), an open-source collaborative database containing nutritional information and ingredient lists for packaged food products worldwide. Data retrieved included energy content (kilocalories per 100g), macronutrients (fat, saturated fat, carbohydrates, sugar, protein per 100g), sodium content (grams per 100g), fiber content (grams per 100g), and complete ingredient lists. For products with ingredient lists in non-English languages, the Google Translate API was utilized to translate ingredients to English for additive detection.

2.2.2 *Health profile development*

Five health profiles were developed to represent high-prevalence chronic conditions in the United States, including cardiovascular disease, which affects ~ 48.6% of adults (35); hypertension, which affects ~ 47% (36); and diabetes, which affects ~ 11.6% (37). The profiles also incorporated common dietary intolerances, including lactose malabsorption, which is a necessary underlying condition for lactose intolerance and affects ~ 68% of the global population (34), as well as less common but clinically important conditions such as chronic kidney disease, irritable bowel syndrome, and asthma. Together, these profiles were designed to demonstrate the versatility of the algorithm across diverse health scenarios.

Profile 1, Control or Baseline, represents a 30-year-old individual weighing 70 kg whose goal is weight maintenance. This individual has no specified diseases or allergies, has a moderate activity level, does not track daily caloric intake, and does not identify hydration as a priority. The

purpose of this profile was to establish baseline FoodByte behavior without disease-specific adjustments.

Profile 2, Diabetes and Weight Loss, represents a 52-year-old individual weighing 85 kg whose goal is weight loss. This individual has type 2 diabetes, has a low activity level, tracks a daily caloric intake of 1,800 kcal, has no specified allergies, and does not identify hydration as a priority. This profile was designed to stress-test the algorithm's sugar penalties, fiber and protein rewards, and refined-grain detection.

Profile 3, Hypertension and Cardiovascular Disease, represents a 60-year-old individual weighing 78 kg whose goal is weight maintenance. This individual has hypertension and cardiovascular disease, has a moderate activity level, tracks a daily caloric intake of 2,000 kcal, has no specified allergies, and does not identify hydration as a priority. This profile was designed to stress-test the sodium tiers, processed-meat detection, saturated-fat penalties, and trans-fat penalties.

Profile 4, IBS and Lactose Intolerance, represents a 28-year-old individual weighing 65 kg whose goal is weight maintenance. This individual has irritable bowel syndrome and lactose intolerance, has a moderate activity level, does not track daily caloric intake, reports a milk allergy, and does not identify hydration as a priority. This profile was designed to stress-test additive overrides for sugar alcohols, high-fructose corn syrup detection, fat-related digestive adjustments, and dairy detection.

Profile 5, CKD and Asthma with High Activity, represents a 45-year-old individual weighing 72 kg whose goal is weight maintenance. This individual has chronic kidney disease and asthma, has a high activity level, tracks a daily caloric intake of 2,200 kcal, has no specified allergies, and identifies hydration as a priority. This profile was designed to stress-test severe additive overrides involving phosphates and sulfites, sodium-related adjustments, and protein handling.

2.3 Comparative analysis methodology

For each of the 50 selected products, the population-level Nutri-Score was obtained from the base nutritional score available through the Open Food Facts API. This population-level value did not include personalization or additive penalties and therefore represented the standardized comparison framework. FoodByte personalized scores were then calculated for each of the five health profiles by combining the base nutritional score, additive penalties, and profile-specific adjustments.

The percentage difference was calculated for every product–profile combination as shown in eq 5, thus yielding 250 total comparisons (50 products x 5 profiles).

$$\text{Percentage Difference} = \frac{|\mathit{FoodByte\ Score} - \mathit{NutriScore}|}{\mathit{NutriScore}} \cdot 100 \quad \text{(eq5)}$$

2.3.1 *Statistical analysis*

Descriptive statistics were computed to summarize score differences between FoodByte and Nutri-Score, including mean percentage difference, standard deviation, minimum, maximum, and range across all food–profile

evaluations. Category-specific and profile-specific summaries were calculated descriptively to characterize structural patterns in score divergence across product types and dietary profiles.

Because each food product was evaluated under each of five health profiles, the data had a cross-classified repeated-measures structure in which observations were potentially correlated through both shared product identity and shared health-profile rule structure. Consequently, treating all 250 product–profile observations as statistically independent would underestimate uncertainty. To account for this dependence, inferential analyses were performed using a cross-classified linear mixed-effects model with score difference (FoodByte score − Nutri-Score) as the outcome. The model included a fixed intercept estimating the overall mean score difference and random intercepts for both product and health profile (eq6),

$$\text{Score difference}_{ij} = \beta_0 + u_{product,i} + v_{profile,j} + \varepsilon_{ij} \qquad \text{(eq6)}$$

where $u_{product,i}$ represents the random intercept for product i, $v_{profile,j}$ represents the random intercept for profile j, and ε_{ij} represents residual variation. This structure accounts for clustering among observations sharing the same food product and among observations sharing the same health-profile rule structure. Variance components were reported for product, profile, and residual variation. Because the products were purposively selected and the five profiles were prespecified rule-based scenarios rather than randomly sampled from defined population frames, generalization is limited to similar packaged-food products and comparable health-profile structures.

Because the 250 observations represented repeated product–profile evaluations rather than independent product samples, the nominal sample size was not interpreted as the effective number of independent observations. To quantify the impact of clustering, an approximate design-effect calculation was performed using the product-level variance proportion estimated by the mixed-effects model. With five profile evaluations per product and product-level clustering accounting for 52.6% of modeled variance, the estimated design effect was $1 + (5 - 1)(0.526) = 3.10$, corresponding to an approximate effective sample size of $250/3.10 \approx 81$ observations. A more conservative approximation incorporating both product- and profile-level variance components yielded an effective sample size of $250/[1 + 4(0.526 + 0.085)] \approx 73$ observations. These calculations are presented as descriptive approximations because cross-classified repeated-measures designs do not have a single exact ICC-based effective sample size. Accordingly, statistical inference was based on the cross-classified mixed-effects model rather than treating all 250 observations as independent.

Standardized effect sizes (Cohen's *d*) and corresponding 95% confidence intervals were calculated separately for each health profile to quantify the magnitude of divergence between FoodByte and Nutri-Score. These effect sizes are presented as descriptive measures of practical magnitude rather than as independent hypothesis tests.

Pearson correlation coefficients and R^2 values were calculated to describe the pooled relationship between FoodByte and Nutri-Score values. Because Pearson correlation assumes independent observations and each product appears repeatedly across profiles, these correlations were treated as descriptive summaries only. No inferential p-values or confidence intervals for correlation coefficients were interpreted.

To assess sensitivity to algorithmic specification, sensitivity analyses were performed by perturbing additive scoring weights (±50%), threshold values (±20%), and profile-specific multipliers for cardiovascular disease penalties (0.5x to 2.0x). For each perturbation, descriptive Pearson correlations between perturbed and original scores were calculated to summarize internal score stability. These correlations were used as descriptive similarity measures only, not as inferential tests. The percentage of products maintaining their letter-grade category under threshold perturbations was also calculated to assess categorical stability.

2.4 Implementation, libraries, and workflow

The implementation used several Python libraries for data acquisition, analysis, statistical modeling, and visualization. The pandas and numpy libraries supported data management, cleaning, numerical calculations, and the computation of percentage differences between FoodByte scores and Nutri-Score. The matplotlib and seaborn libraries were used to create profile-comparison boxplots, category-specific grouped bar charts, regression scatter plots with annotated outliers, effect-size plots with confidence intervals, and sensitivity-analysis heatmaps. The scipy.stats module supported descriptive statistics, Pearson correlation calculations, and bootstrap resampling for effect-size confidence intervals, while statsmodels was used to estimate linear mixed-effects models that accounted for the repeated-measures structure. The requests and googletrans libraries facilitated programmatic access to the Open Food Facts API and translation of non-English ingredient lists during dataset assembly.

The analytical workflow began with data preparation, during which product data, Nutri-Score values, FoodByte scores across the five health profiles, and product-category labels were imported and cleaned. Percentage differences between FoodByte and Nutri-Score were then calculated for every health profile to quantify personalization effects.

The statistical analysis included descriptive calculations of the mean, standard deviation, median, minimum, maximum, and range across all comparisons. Inferential analysis was performed using a cross-classified linear mixed-effects model in which score difference was the outcome and random intercepts were included for both product and health profile. Cohen's *d* values and bootstrap confidence intervals based on 10,000 iterations were calculated for each health profile. Pearson correlation coefficients and R^2 values were reported as descriptive summaries of the pooled relationship between Nutri-Score and FoodByte scores; inferential correlation testing was not interpreted because observations were repeated across profiles. Sensitivity analyses evaluated robustness to changes in additive weights, disease-specific thresholds, and profile-specific penalty multipliers. Finally, category- and profile-specific analyses were performed to identify the

product categories and health profiles showing the largest descriptive deviations from Nutri-Score within the evaluated sample.

3. Results

3.1 Overall comparative analysis

Analysis of 50 food products across 5 health profiles yielded 250 total product–profile combinations. The comparative analysis showed that FoodByte personalized scores often differed from population-level Nutri-Score ratings, particularly for health profiles involving disease-specific sodium, sugar, fat, additive, or allergen-related adjustments.

Overall descriptive statistics demonstrated substantial divergence between the two scoring frameworks. Across the evaluated product–profile combinations, the mean percentage difference was 29.18%, with a standard deviation of 32.40%. The median percentage difference was 14.73%, and observed values ranged from 0.00% to 97.74%.

A cross-classified linear mixed-effects model was used to account for the repeated-measures structure of the data, with random intercepts for both product and health profile. This model estimated an overall mean score difference of -10.49 points, indicating that FoodByte scores were lower than Nutri-Score values on average across the evaluated product–profile combinations. The 95% confidence interval for the mean difference was [-14.50, -6.48], with a model-based p-value of 2.88×10^{-7}. These results indicate a consistent divergence between FoodByte and Nutri-Score after accounting for clustering by both food product and health-profile rule structure.

Variance-component estimates indicated that product-level clustering accounted for 52.6% of modeled variance, profile-level clustering accounted for 8.5%, and residual variation accounted for 38.9%. Thus, product identity was the largest modeled source of clustering, while health-profile structure also contributed measurable variance and was retained in the random-effects structure. These variance components should be interpreted as model-based clustering estimates rather than causal attribution.

Although the dataset contained 250 product–profile observations, these observations were clustered by both product and profile and should not be interpreted as 250 independent samples. Using the product-level variance proportion as an approximate ICC-like clustering estimate, the design effect was 3.104, giving an ~ effective sample size of 80.5. A more conservative approximation incorporating both product- and profile-level variance components yielded a design effect of 3.443 and an ~ effective sample size of 72.6. These estimates indicated that the effective information content was substantially lower than the nominal observation count, supporting cautious interpretation of model-based inference.

Model convergence and residual diagnostics were assessed for the cross-classified mixed-effects model. The model converged successfully. Residual diagnostics were generally acceptable: the residual Q-Q plot showed approximate normality with mild tail deviations, and the residuals-versus-fitted plot showed residuals centered ~ around zero, although several outlying observations and some visible structure were present. The Shapiro-Wilk test did not indicate strong

evidence against residual normality (W = 0.991, p = 0.136). These diagnostics support cautious interpretation of the model estimates rather than claims of perfect model fit.

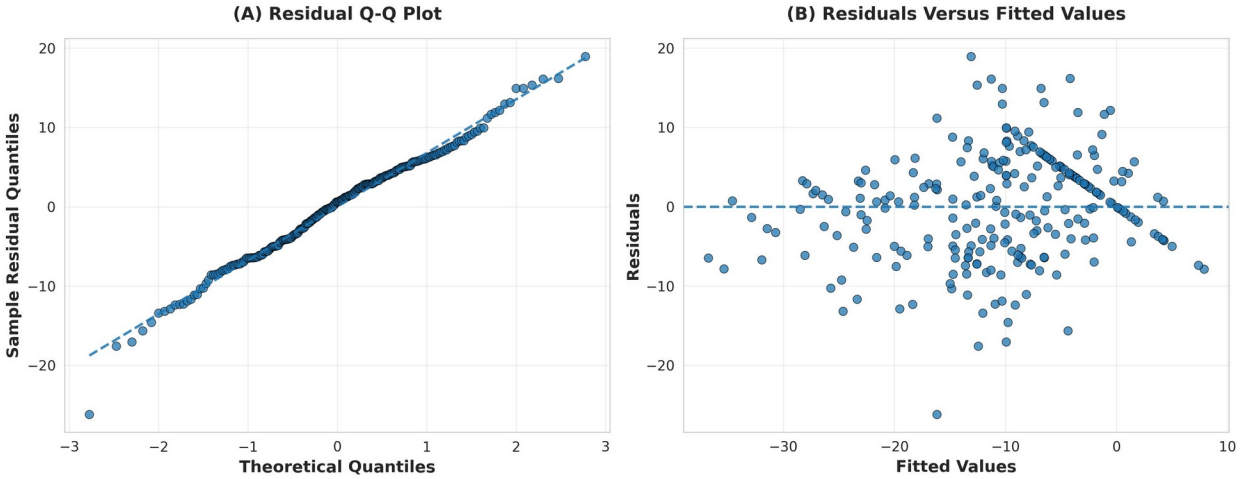

Figure 1. Diagnostic plots for the cross-classified mixed-effects model. The model included random intercepts for both product and health profile and used score difference, defined as FoodByte score minus Nutri-Score, as the outcome. (**A**) Residual Q-Q plot comparing model residual quantiles with theoretical normal quantiles. Most residuals follow the reference line, suggesting approximate normality, with mild tail deviations and one stronger lower-tail outlier. (**B**) Residuals versus fitted values plot. Residuals are centered approximately around zero, although several outlying observations and some visible structure are present. The model converged successfully, and the Shapiro-Wilk test did not indicate strong evidence against residual normality (W = 0.991, p = 0.136).

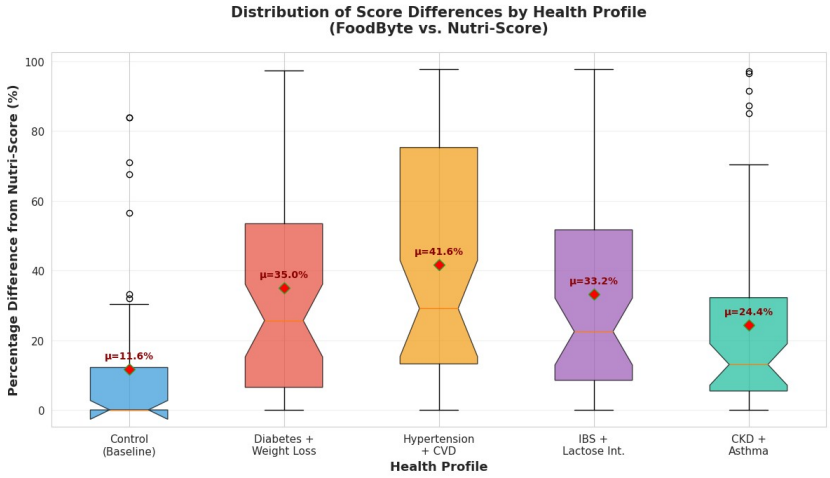

Figure 2. Distribution of percentage differences between FoodByte and Nutri-Score across five health profiles. Box plots show median (center line), interquartile range (box), range (whiskers), and outliers (circles). Red diamonds indicate mean values. Control profile shows 11.6% mean difference; disease-specific profiles range from 24.4–41.6%, showing larger mean divergence for disease-specific profiles than for the Control profile in this sample.

The asymmetric distribution and long upper tail demonstrate that while some products align closely with Nutri-Score, many experienced extreme reclassification under personalized evaluation, particularly for disease-vulnerable profiles.

3.2 Profile-specific analysis

Stratification by health profile found that personalization consistently amplified divergence, particularly for conditions sensitive to sodium, sugar, and fat composition, as seen in Table 1.

Table 1. Effect sizes and statistical comparisons by health profile

Profile	n	Mean Diff (SD)	95% CI	Cohen's d	95% CI (d)	Mean % Diff (SD)	95% CI (%)
Control (Baseline)	50	-4.92 (8.68)	[-7.39, -2.45]	-0.567	[-0.740, -0.414]	11.6 (22.8)	[5.1, 18.1]
Diabetes + Weight Loss	50	-11.80 (11.48)	[-15.07, -8.54]	-1.028	[-1.378, -0.769]	35.0 (33.9)	[25.4, 44.7]
Hypertension + CVD	50	-14.16 (14.83)	[-18.38, -9.95]	-0.955	[-1.332, -0.673]	41.6 (34.6)	[31.8, 51.5]
IBS + Lactose Intolerance	50	-12.64 (10.50)	[-15.62, -9.66]	-1.204	[-1.538, -0.979]	33.2 (33.6)	[23.7, 42.8]
CKD + Asthma	50	-8.93 (11.02)	[-12.06, -5.79]	-0.810	[-1.062, -0.609]	24.4 (28.0)	[16.4, 32.4]

Effect size analysis showed that the magnitude of divergence suggests practical relevance within the evaluated sample. Four of five profiles had large descriptive standardized differences (Cohen's $|d| > 0.8$), while the Control profile had a medium descriptive effect size ($d = -0.567$). These effect sizes are reported to contextualize the size of the observed score differences rather than as independent hypothesis tests. Disease-specific profiles showed larger divergence than the Control profile: Diabetes + Weight Loss ($d = -1.028$), HTN + CVD ($d = -0.955$), IBS + Lactose Intolerance ($d = -1.204$), and CKD + Asthma ($d = -0.810$). The large effect for IBS + Lactose Intolerance reflects the combined impact of dairy-related penalties and FODMAP-sensitive additive adjustments in the FoodByte rule set.

Disease-specific profiles showed substantially larger effect sizes than the control baseline, with the IBS + Lactose Intolerance profile demonstrating the most extreme divergence ($d = -1.204$, 95% CI: [-1.538, -0.979]). This reflects the compounding impact of dairy elimination penalties and FODMAP-sensitive additive adjustments. The consistently negative effect sizes across profiles indicated that FoodByte assigned lower scores than Nutri-Score for many evaluated products when additive burden and profile-specific scoring rules were incorporated. Because Nutri-Score does not evaluate additive-related risk or disease-specific nutritional requirements, it necessarily underestimates these dimensions of risk relative to FoodByte's rule-based scoring framework. The present study demonstrates this algorithmic difference but does not establish that either system more accurately predicts clinical outcomes.

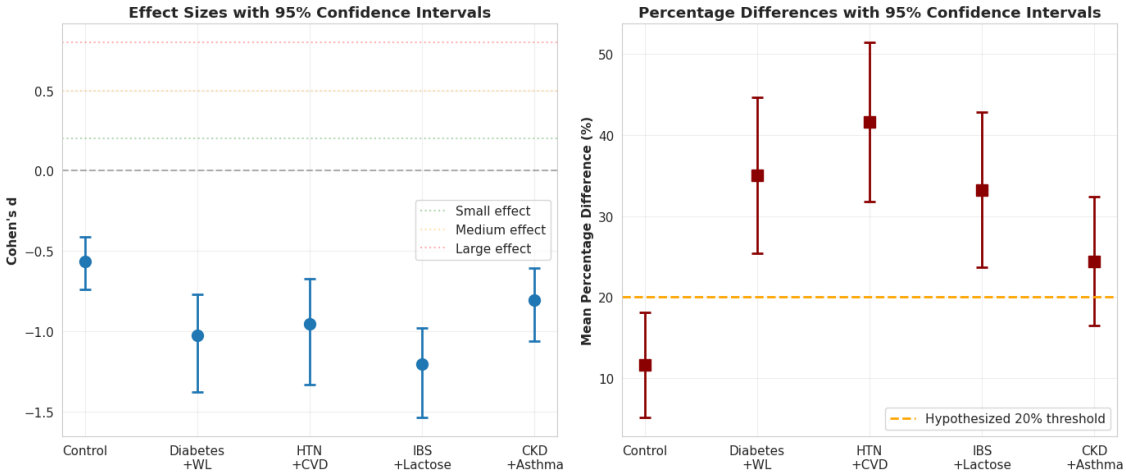

Figure 3. Effect sizes and percentage differences with 95% confidence intervals across health profiles. The first plot demonstrates Cohen's d values with bootstrap confidence intervals (10,000 iterations). The reference lines indicate small (d = 0.2), medium (d = 0.5), and large (d = 0.8) effect thresholds. Four of five profiles demonstrate large effects (|d| > 0.8), with IBS + Lactose Intolerance showing the largest effect (d = -1.204). The second plot demonstrates mean percentage differences with 95% confidence intervals. Disease-specific profiles exceeded the prespecified 20% discrepancy threshold in this sample, while the Control profile showed a smaller mean percentage difference. Negative Cohen's d values indicate FoodByte assigns systematically lower scores than Nutri-Score.

3.3 Category-specific analysis

Products were further analyzed by food category to identify where personalized scoring produced the greatest divergence from population-level evaluation (Table 2). Products exhibiting the greatest divergence frequently contained multiple artificial colors that triggered hyperactivity-related penalties (12), high sodium concentrations that triggered hypertension-specific penalties, and high saturated-fat concentrations that triggered cardiovascular-disease penalties. In contrast, grain-based products exhibited the lowest divergence. Minimally processed items such as quinoa, pasta, and oats maintained favorable nutritional profiles across all health conditions, resulting in consistent scores between systems.

Table 2. Mean percentage difference by product category

Category	n	Mean Diff (%)	Representative Products
Snacks	23	41.40	Doritos, Pringles, Cheez-Its
Beverages	5	24.40	Soda, Juice, Sports Drinks
Breakfast	5	20.61	Oats, Cereals, Mac ‘n Cheese
Condiments	5	19.01	Mayo, Hummus, Marinara
Dairy	7	18.76	Yogurt, Cottage Cheese, Cream
Grains	5	11.02	Granola Bars, Fig Bars

This pattern suggests that the largest score differences occurred in categories with more complex ingredient profiles and higher additive burden (Figure 4). Because the products were purposively selected, these category patterns should be interpreted descriptively rather than as population-level estimates of scoring performance.

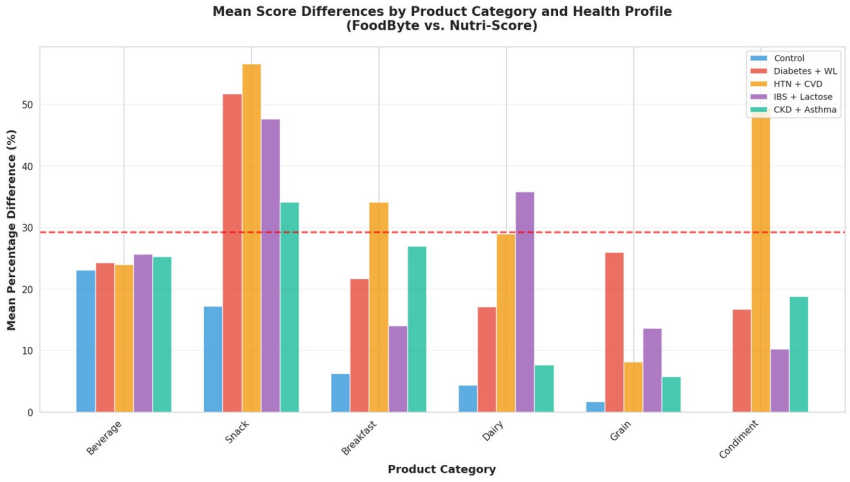

Figure 4. Mean percentage differences by product category across five health profiles. The red dashed line indicates the overall mean (29.18%).

3.4 Additive detection and prevalence

Analysis of additive presence across the 50-product sample found that 8% of products, or 4 of 50, contained at least one high-risk additive with a risk score of 8 or greater. An additional 24%, or 12 of 50 products, contained at least one moderate-risk additive with a risk score between 5 and 7. Furthermore, 30% of products, or 15 of 50, contained three or more additives of any risk level.

Artificial colors, including Red 40, Yellow 5, Yellow 6, Blue 1, and Blue 2, were the most frequently detected high-risk additive class and appeared in seven products, representing 14% of the sample. Artificial sweeteners, including aspartame, acesulfame potassium, and sucralose, appeared in five products, representing 10% of the sample. Flavor enhancers, particularly monosodium glutamate, appeared in three products, representing 6% of the sample. Skittles received a total additive penalty of 25 points because titanium dioxide, Red 40, Yellow 5, Yellow 6, Blue 1, and Blue 2 were detected. Strawberry Ring Pop also received a total penalty of 25 points because it contained Red 3, Red 40, Blue 1, and titanium dioxide. Pringles received a total penalty of 25 points because monosodium glutamate, disodium inosinate, disodium guanylate, yeast extract, and dextrose were detected.

3.5 Case study: Nacho cheese Doritos

Nacho Cheese Doritos contained 530 kcal, 28.3 g of total fat, 3.53 g of saturated fat, 3.53 g of sugar, 600 mg or 0.6 g of sodium, 7.07 g of protein, and 3.53 g of fiber per 100 g. Under Nutri-Score, the product received a normalized score of 44.2 out of 100 and a grade of D. Nutri-Score therefore categorized Nacho Cheese Doritos as a relatively unfavorable product but

did not incorporate its additive burden or apply disease-specific profile rules.

Under the FoodByte Control profile, the product received a final score of 19.2 out of 100, equivalent to an E or "Very Poor" classification. This represented a 56.56% decrease relative to its Nutri-Score score. The score consisted of the 44.2-point Nutri-Score baseline, a 25-point additive penalty, no disease-specific adjustment, and a final FoodByte score of 19.2. Because the Control profile includes no disease-specific penalties, this reduction demonstrated that the additive-penalty component alone could substantially alter the product's evaluation.

FoodByte detected seven additives contributing to the cumulative penalty. Red 40 and Yellow 6 each had a risk score of 7.0 and were classified as moderate-risk artificial colors. Yellow 5 had a risk score of 6.0 and was classified as a low-to-moderate-risk artificial color. Monosodium glutamate had a risk score of 6.0 and was classified as a low-to-moderate-risk flavor enhancer. Disodium inosinate and disodium guanylate each had a risk score of 5.0 and were classified as low-to-moderate-risk flavor enhancers. Dextrose had a risk score of 5.0 and was classified as a low-to-moderate-risk refined sugar.

Although none of these additives was individually classified as presenting "extreme risk," their co-occurrence produced a large cumulative penalty. This approach reflects emerging evidence that combined exposure to artificial dyes and flavor enhancers may contribute to neurological, metabolic, or behavioral effects, particularly among children and sensitive populations. Nutri-Score does not incorporate this ingredient-level additive information.

When evaluated under the disease-specific profiles, Nacho Cheese Doritos was assigned a score of 1.0 out of 100 for the Hypertension and Cardiovascular Disease profile, representing a 97.74% decrease from Nutri-Score; a score of 10.36 out of 100 for the Diabetes and Weight Loss profile, representing a 76.56% decrease; and a score of 1.0 out of 100 for the IBS and Lactose Intolerance profile, representing a 97.74% decrease.

These lower FoodByte scores were produced by several components of the rule set. The product contained 600 mg of sodium per 100 g, exceeding the sodium thresholds used in the hypertension profile. It also contained several sodium-containing additives, including monosodium glutamate, disodium inosinate, and disodium guanylate, which contributed to the additive assessment in addition to the labeled sodium concentration. Artificial colorants further contributed to the additive penalty. Thus, under FoodByte's rule-based framework, Nacho Cheese Doritos received substantially lower scores for multiple disease-specific profiles than under the population-level Nutri-Score framework.

3.6 Product-level stability and disease-specific personalization

Variance component analysis from the cross-classified mixed-effects model indicated that differences between food products accounted for the largest proportion of variability in FoodByte–Nutri-Score score differences (52.6%), whereas health-profile effects accounted for 8.5%, with the remaining variance attributable to residual factors. This indicates

that intrinsic nutritional characteristics of individual foods establish the primary baseline for scoring. However, examination of individual products demonstrated that disease-specific personalization substantially modified recommendations for selected foods (Table 3 and section 3.5). For example, Sea Salt Popped Corn Snacks received an identical FoodByte score across all five health profiles (69.4), indicating no disease-specific adjustment, whereas JIF Peanut Butter exhibited a 42.4-point range across profiles, primarily because the hypertension/cardiovascular profile received a substantially lower score than the remaining profiles. Similarly, Nacho Cheese Doritos and Pringles exhibited profile-dependent score ranges exceeding 34 points, reflecting substantial disease-specific adjustments despite having fixed underlying nutritional compositions. These findings indicate that FoodByte does not simply classify foods as universally healthy or unhealthy; rather, it preserves stable recommendations for foods with broad nutritional suitability while selectively modifying scores for products whose ingredient composition has differential relevance across specific health conditions.

Table 3. Representative examples demonstrating disease-specific personalization by FoodByte compared with the static Nutri-Score framework

Product	Nutri-Score (0–100)	FoodByte Range Across Profiles (difference from Nutri-Score)	Disease(s) with Little/No Change	Disease(s) with Maximum Change	Interpretation
Sea Salt Popped Corn Snacks	69.4	69.4–69.4 (0.0)	All profiles	None	FoodByte agrees with Nutri-Score that this food is broadly suitable; no personalization required.
Coconut Water	78.4	73.4–81.4 (8.0)	HTN/CVD, IBS	CKD/Asthma	Minor disease-specific adjustment while preserving a generally favorable recommendation.
Dave's Killer Bread	74.8	64.6–74.8 (10.2)	Diabetes, IBS, CKD/Asthma	HTN/CVD	Broadly healthy food with modest disease-specific adjustment.
Old Fashioned Quaker Oats	82.0	82.0–93.6 (11.6)	IBS, CKD/Asthma	HTN/CVD	Healthy baseline retained; disease profile provides modest refinement.
Rao's Marinara Sauce	65.8	49.9–65.8 (15.9)	Diabetes, IBS	HTN/CVD	Mostly stable recommendation with targeted cardiovascular adjustment.
JIF Peanut Butter	56.8	14.5–56.8 (42.4)	Diabetes, IBS, CKD/Asthma	HTN/CVD	Personalized scoring substantially reclassifies suitability for cardiovascular disease.
Nacho Cheese Doritos	44.2	1.0–44.2 (43.2)	None	HTN/CVD, IBS	FoodByte identifies disease-specific nutritional concerns that Nutri-Score cannot distinguish.
Pringles Sour Cream & Onion	35.2	1.0–35.2 (34.2)	None	Diabetes, HTN/CVD, IBS, CKD/Asthma	Uniform Nutri-Score replaced by profile-dependent recommendations reflecting disease-specific risks.

3.6 Correlation Analysis and Regression

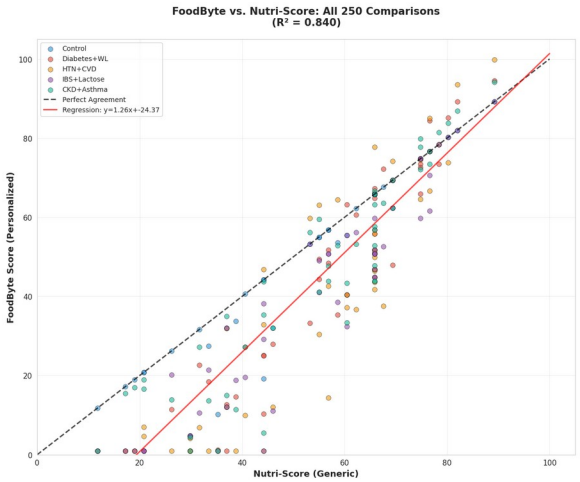

Figure 5. Scatter plot of all 250 product-profile combinations comparing Nutri-Score (x-axis) to FoodByte (y-axis). The black dashed line represents perfect agreement, while the red line shows regression (y = 1.26x – 24.37).

Descriptively, FoodByte and Nutri-Score showed a strong linear association across the pooled product–profile observations (Pearson r = 0.916; R^2 = 0.840) (Figure 5). Because each product appears repeatedly across health profiles, these correlation and regression results are presented as descriptive summaries only; no inferential test, confidence interval, or independence-based interpretation is attached to the correlation.

The pooled regression line (FoodByte = 1.26 × Nutri-Score - 24.37) suggests that FoodByte scores tended to be lower than Nutri-Score values for many low- and mid-range products in this sample. This pattern is consistent with FoodByte's additive penalties and profile-specific adjustments, which are not part of Nutri-Score's population-level nutrient-profiling design.

Despite the high descriptive correlation, the scatter plot shows systematic score divergence for several products and profiles. Annotated outliers, including ultra-processed snack products, illustrate cases in which FoodByte assigned substantially lower scores than Nutri-Score under specific profile rules. Inferential analysis accounting for repeated measures by both product and profile is reported separately using the cross-classified mixed-effects model in Section 3.1.

3.7 Sensitivity and robustness analyses

To evaluate whether observed differences between FoodByte and Nutri-Score depend critically on specific algorithmic parameters, three sensitivity analyses were systematically performed perturbing key components of the scoring system.

3.7.1 *Additive weight perturbation*

To assess sensitivity to the rule-based heuristic additive weights, FoodByte scores were recalculated after additive penalties were multiplied by 0.5, representing a 50% reduction,

and by 1.5, representing a 50% increase. The descriptive Pearson correlations between the original and perturbed scores remained close to 1.0 across all five profiles. Under the 50% reduction in additive weights, the mean correlation was $r = 0.987$, with profile-specific correlations ranging from 0.983 to 0.992. Under the 50% increase in additive weights, the mean correlation was $r = 0.993$, with profile-specific correlations ranging from 0.990 to 0.996.

These descriptive correlations suggest that FoodByte score patterns were internally stable under the tested additive-weight perturbations and were not highly sensitive to the precise additive-penalty scaling applied in this study. However, these sensitivity results do not validate the additive weights against clinical outcomes or establish that the weights represent empirically calibrated estimates of health risk.

3.7.2 *Threshold perturbation*

Disease-specific thresholds (e.g., sodium limits for hypertension, sugar limits for diabetes) reflect clinical guideline targets but may require adjustment based on individual circumstances. To test categorical stability, all thresholds were perturbed by ±20% and any changes in letter-grade categories were determined.

Under these perturbations, 90.4% of product evaluations maintained their original letter grade, while 9.6% changed by one category, such as from C to D or from D to C. No product evaluation changed by more than one letter-grade category. Category changes occurred primarily for products with scores near category boundaries (e.g., 49-51 near the C/D threshold at 50). Products with extreme scores (very high or very low) remained stable, confirming that clear-cut recommendations were robust to moderate threshold adjustments.

3.7.3 *Cardiovascular disease profile sensitivity*

To illustrate profile-specific robustness, the HTN + CVD profile was examined under varying penalty multipliers from 0.5x to 2.0x, representing conservative to aggressive disease-specific adjustments. Correlations between original and perturbed scores remained above r = 0.978 for all realistic multipliers (0.75x to 2.0x) (Table 4).

Table 4. Cardiovascular disease profile sensitivity to penalty multipliers

Multiplier	Mean Score	Correlation
0.50x	46.87	0.983
0.75x	43.33	0.997
1.00x	39.79	1.000
1.25x	36.25	0.998
1.50x	32.71	0.992
2.00x	25.63	0.979

Product rankings remained highly stable (Pearson r > 0.90) across the entire tested range, indicating that relative product assessments for cardiovascular disease were preserved even under substantial variations in penalty severity.

3.7.4 *Sensitivity summary*

Figure 6 presents a heatmap of Pearson correlations between original FoodByte scores and scores obtained under a range of algorithmic perturbations across all tested health profiles. Across the 35 perturbation–profile combinations, correlations were uniformly high ($r \geq 0.983$), with the majority exceeding $r = 0.99$, indicating minimal sensitivity of product rankings to parameter variation.The uniformly high descriptive correlations across perturbation–profile combinations indicate that FoodByte's product rankings were internally stable under the tested parameter changes. These sensitivity analyses support the internal robustness of the scoring outputs to selected algorithmic perturbations, but they do not validate the scores against clinical outcomes or establish superiority over existing food-labeling systems.

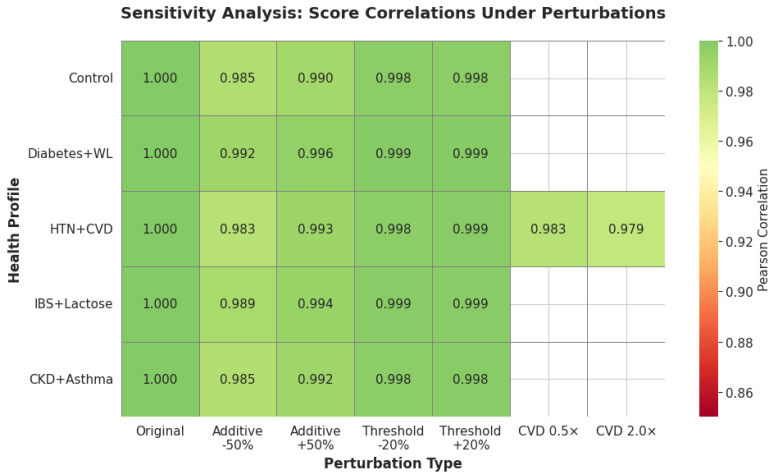

Figure 6. Sensitivity analysis heatmap showing Pearson correlations between original FoodByte scores and perturbed scores under various algorithmic modifications. Columns represent perturbation types: Original (baseline), Additive -50%/+50% (scaled additive penalties), Threshold -20%/+20% (adjusted disease-specific thresholds), and CVD 0.5x/2.0x (cardiovascular penalty multipliers, HTN+CVD profile only). All correlations exceed r = 0.983 (green cells), indicating high stability of product rankings across perturbations. White cells indicate non-applicable perturbations (CVD multipliers for non-CVD profiles).

3.7.5 *Aggregation rule considerations*

Model sensitivity may also depend on the method used to aggregate multiple additive penalties (e.g., simple summation, capped summation, maximum-risk-only, or class-weighted aggregation). Alternative aggregation rules were not evaluated because the additive-weight, threshold, and profile-multiplier perturbations already stress-tested the effective behavior of the aggregation mechanism across a wide parameter range, and meaningful comparison would require full re-execution of the FoodByte algorithm rather than heuristic simulation. The consistently high descriptive rank correlations and limited category instability suggest that the observed score patterns are not driven by a single aggregation choice. Future work should evaluate alternative aggregation strategies through complete algorithmic implementation and validate scoring performance against behavioral and clinical outcomes.

4. Discussion

4.1 Principal findings

This study found that personalized, additive-aware nutritional scoring produced consistent divergence from Nutri-Score across the evaluated product–profile combinations. Across 250 product–profile combinations, FoodByte diverged from Nutri-Score by an average of 29.18%. In a cross-classified mixed-effects model with random intercepts for both product and health profile, FoodByte scores were lower than Nutri-Score values by an average of 10.49 points (95% CI: [-14.50, -6.48]; model-based $p = 2.88 \times 10^{-7}$). These findings suggest that FoodByte and Nutri-Score generated different score outputs in this sample, particularly when additive burden and profile-specific scoring rules were incorporated. Because the products were purposively selected and the profiles were prespecified rule-based scenarios, these results should be interpreted as evidence of divergence within the evaluated sample rather than proof of broad clinical superiority or population-wide generalizability.

The magnitude of divergence suggests practical relevance within the evaluated sample. Four of five health profiles had large descriptive standardized differences (Cohen's $|d| > 0.8$), with IBS + Lactose Intolerance showing the largest effect size ($d = -1.204$, 95% CI: [-1.538, -0.979]). The Control profile, which received additive penalties without disease-specific adjustments, had a medium effect size ($d = -0.567$, 95% CI: [-0.740, -0.414]). These effect sizes indicate sizable score differences under the FoodByte scoring rules, but they should not be interpreted as evidence of clinical outcome improvement.

Sensitivity analyses suggested internal stability of FoodByte score outputs under selected algorithmic perturbations. Descriptive Pearson correlations remained high under ±50% changes to additive weights, and 90.4% of products maintained their letter-grade category under ±20% threshold perturbations. Cardiovascular disease penalty multipliers varied from 0.5x to 2.0x while maintaining high descriptive similarity to the original scores. These analyses support internal robustness of the scoring outputs under the tested perturbations, but they do not validate the scoring rules against clinical outcomes.

Although FoodByte and Nutri-Score were strongly correlated descriptively ($r = 0.916$), the pooled scatter plot and regression line showed systematic score divergence rather than redundancy. The fitted descriptive regression line (FoodByte = 1.26 × Nutri-Score − 24.37) suggests that FoodByte tended to assign lower scores to many low- and mid-range Nutri-Score products in this sample. This pattern reflects the additional additive penalties and profile-specific rules included in FoodByte, rather than evidence that one system is clinically superior.

A potential interpretation of the variance-component analysis is that disease-specific personalization contributes relatively little because product identity accounted for the largest proportion of variability in FoodByte–Nutri-Score score differences. However, this interpretation overlooks the purpose of a personalized nutritional scoring system. Product identity establishes the baseline nutritional quality of a food, whereas personalization determines whether that baseline should be modified for individuals with specific health conditions. Indeed, several products, such as

Sea Salt Popped Corn Snacks, received identical scores across all five health profiles, indicating that their nutritional suitability was largely independent of disease status. In contrast, other products exhibited substantial disease-specific reclassification. JIF Peanut Butter demonstrated a 42-point score range across health profiles because the hypertension /cardiovascular profile applied penalties for sodium and saturated fat that were not equally relevant to the other profiles. Similarly, the Nacho Cheese Doritos case study illustrates how FoodByte's rule-based framework can substantially alter the evaluation of a highly processed snack. Under the cardiovascular profile, Doritos received a FoodByte score of 1/100 because of sodium content, saturated fat, and additive penalties, whereas less restrictive profiles produced higher scores. These findings indicate that FoodByte is not intended to reinterpret every food differently for every individual. Rather, it selectively identifies foods whose nutritional characteristics interact with disease-specific dietary considerations while preserving consistent recommendations for foods whose suitability is largely independent of health status. A universal food-labeling system should produce similar recommendations for foods that are broadly appropriate for most consumers. The value of a personalized system, such as FoodByte is therefore not that it changes every recommendation, but that it correctly identifies the subset of foods for which disease-specific nutritional considerations justify a different recommendation.

The observed divergence from Nutri-Score reflects FoodByte's design rather than recalibration of conventional nutrient profiling. FoodByte extends population-level nutrient profiling by combining literature-informed, rule-based additive-risk assessment with disease-specific nutritional adjustments informed by published clinical guidelines and supporting literature for diabetes (26), hypertension (28,29), cardiovascular disease (31,32), chronic kidney disease (33,34), IBS (35), and asthma (12), together with goal- and activity-based personalization. Scores are reported on a transparent continuous 1–100 scale using published equations. The weighting scheme and disease-specific thresholds represent literature-informed heuristic operationalizations rather than clinically validated decision thresholds and therefore require prospective clinical validation.

4.2 Implications for public health

Additive-aware scoring may provide information not captured by conventional nutrient-profiling systems, particularly given international differences in additive regulation (6, 7, 24, 36). Because this study analyzed a purposive sample of 50 products, it does not estimate population-level additive exposure or health risk. Nevertheless, presenting additive-related information in an accessible format may improve consumer understanding beyond conventional ingredient lists, although its effectiveness requires behavioral validation.

FoodByte also addresses a limitation of population-level food scoring by incorporating disease-specific personalization. Individuals with diabetes (37), cardiovascular disease (35), and other chronic conditions have nutritional requirements that differ from those of the general population, whereas conventional systems assign identical scores regardless of health status. Whether personalized scoring improves dietary decisions or clinical outcomes remains to be established through prospective studies.

Because chronic diseases account for approximately 90% of the United States' $4.9 trillion in annual healthcare expenditures (38), personalized food-scoring systems that improve dietary decision-making could have important public health and economic implications. However, this potential should be evaluated through clinical and cost-effectiveness studies before conclusions regarding healthcare impact can be drawn.

4.3 Comparison with existing food scoring systems and consumer apps

4.3.1 *Scope differences relative to Nutri-Score*

Although Nutri-Score represents an advancement over conventional nutrition-facts labels alone, it differs from FoodByte in several important design respects. Nutri-Score does not include an additive-risk scoring layer and is not designed to personalize product ratings according to an individual health profile. Its A–E categories summarize nutrient profiling in a simplified format, but it does not provide the same type of ingredient-level explanation implemented in FoodByte. Allergen handling also falls outside the central Nutri-Score scoring framework.

Peters and Verhagen (2022) noted that Nutri-Score's scientific substantiation is questionable for certain food categories and may create misleading health perceptions (8). The present findings are consistent with these scope differences: FoodByte and Nutri-Score diverged most for profiles where FoodByte applies additive-aware or disease-specific scoring rules. This divergence should not be interpreted as evidence that Nutri-Score misrates products, because Nutri-Score was not designed to perform individualized clinical or additive-risk assessment.

4.3.2 *Comparison with consumer nutrition applications*

Beyond Nutri-Score, consumer-facing applications such as Yuka have gained popularity, although nutrition experts have questioned the scientific rigor, consistency, and transparency of their scoring methodologies (17). Like FoodByte, Yuka currently applies additive penalties without considering concentration despite the toxicological principle that "the dose makes the poison" (39), a limitation also noted by Lambert (40). Because Open Food Facts generally reports additive presence rather than concentration, FoodByte likewise functions as an additive-aware screening tool rather than a quantitative dose-response model. Future work should incorporate concentration data to enable concentration-dependent risk assessment.

Additional criticisms of Yuka include awarding an organic bonus despite limited evidence that organic foods are nutritionally superior (17–19), providing identical scores regardless of individual health status (20), and using categorical labels that may promote unhealthy relationships with food (20,36,41). Simplified health claims have also been the subject of legal scrutiny (42). In contrast, FoodByte evaluates products using nutritional composition, additive-related information, and disease-specific personalization while reporting neutral numerical scores with transparent rule-based explanations. Nevertheless, FoodByte's outputs remain heuristic algorithmic estimates rather than clinically validated measures of individual health risk.

Other food-labeling systems have complementary limitations. NOVA classifies foods by processing level but does not generate nutritional scores or evaluate additive-related risks (11), while the Health Star Rating system provides nutrient-based ratings without additive-risk assessment or personalization (43).

4.5 Limitations

This study has several limitations. First, the dataset consisted of 50 purposively selected packaged foods evaluated across five prespecified health profiles, yielding 250 product–profile observations. Because each product was evaluated repeatedly across profiles and each profile was repeatedly applied across products, the observations were clustered rather than independent. The mixed-effects model estimated that product- and profile-level clustering accounted for 52.6% and 8.5% of modeled variance, respectively, corresponding to an approximate effective sample size of 73–81 independent observations. Accordingly, statistical precision and generalizability should be interpreted cautiously, and future studies should employ larger, randomly or stratified sampled product datasets.

Second, the health profiles represent predefined archetypes rather than real consumers and therefore cannot capture the full heterogeneity of comorbidities, medication use, disease severity, cultural dietary practices, food accessibility, or demographic differences. Consequently, the framework demonstrates how personalization changes algorithmic scoring but does not establish improved dietary guidance or health outcomes in real populations. Validation using consumers with chronic diseases is needed.

Third, additive-risk scores are literature-informed, rule-based heuristic weights rather than empirically estimated clinical risk coefficients. The current implementation relies primarily on binary additive detection because concentration data are generally unavailable in the Open Food Facts database. It also does not model cumulative exposure, dose-response relationships, or interactions among additives. Although epidemiological evidence supports risks associated with processed meats (30), refined grains (30), sodium benzoate–vitamin C interactions (24), artificial colors with sodium benzoate (11), and evolving evidence such as the IARC classification of aspartame (20), these findings cannot yet be translated into individualized quantitative risk estimates within the current framework. Future versions should incorporate additive concentrations, synergistic interactions, food-category–level risk integration, and updated toxicological evidence as it becomes available.

Fourth, algorithm performance depends on the completeness and accuracy of the Open Food Facts database. Missing nutrient values, translated ingredient lists, and incomplete additive declarations may affect scoring accuracy. Improved ingredient parsing, multilingual validation, and automated recognition of synonymous additive names would strengthen future implementations.

Finally, this study evaluated algorithmic behavior rather than clinical utility. Although FoodByte demonstrated systematic divergence from Nutri-Score and internal robustness under selected parameter perturbations, these findings should not be interpreted as evidence of clinical superiority or improved health outcomes. Future studies should evaluate consumer

comprehension, purchasing behavior, long-term adherence, clinician assessment, and clinical endpoints such as HbA1c, blood pressure, and weight change to determine whether personalized food scoring provides measurable benefits beyond conventional nutrient-profiling systems.

4.6 Future research directions

Future work should evaluate FoodByte using larger and more representative food datasets, incorporate quantitative additive concentration data, improve ingredient parsing, and explore alternative scoring and aggregation strategies. More importantly, future studies should determine when personalized food scoring provides meaningful advantages over population-level nutrient-profiling systems by evaluating whether disease-specific recommendations improve clinician agreement, consumer decision-making, dietary behavior, and clinical outcomes. Such investigations should also identify the food categories and clinical contexts in which personalization materially changes recommendations versus those for which conventional nutrient-profiling systems remain sufficient. These studies will establish the practical value and appropriate scope of personalized, additive-aware food scoring beyond demonstrating algorithmic divergence.

5. Conclusion

FoodByte extends conventional front-of-package nutrient profiling by incorporating disease-specific dietary considerations, food additives, and allergen sensitivities into a personalized scoring framework. Unlike Nutri-Score, which assigns a single population-level score to each food regardless of individual health status, FoodByte selectively modifies recommendations when disease-specific nutritional characteristics justify an alternative assessment while preserving consistent recommendations for foods broadly suitable across health profiles. This capability enables FoodByte to distinguish foods that require individualized evaluation from those appropriately represented by a universal nutritional score. The observed systematic divergence from Nutri-Score therefore reflects an expansion of functionality rather than a recalibration of the same scoring paradigm. Although clinical validation remains necessary, these findings demonstrate that FoodByte provides a more comprehensive framework for personalized nutritional decision support than static population-based nutrient-profiling systems. Future studies should evaluate whether this personalized approach improves dietary decision-making, clinician agreement, and health outcomes.

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Code availability

The FoodByte source code, processed dataset, and analysis scripts used to reproduce all statistical analyses and figures are publicly available at the project's GitHub repository at https://github.com/harshithapoludas/FoodByte.git

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