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Nutritional Value Score Rates Foods Based on Nutrient Density and Noncommunicable Disease Prevention

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A B S T R A C T

Background: Most nutrient profiling systems (NPS) were designed exclusively for high-income countries to address chronic-disease risk and do not capture locally available foods, nutrient bioavailability, or the dual burden of undernutrition and noncommunicable diseases in low- and middle-income countries (LMICs).

Objectives: We developed and tested the Nutritional Value Score (NVS)—a novel NPS based on priority nutrients and dietary factors predictive of noncommunicable disease risk—to better identify foods with high nutritional value relevant to health priorities in high-income countries and LMICs alike, and to serve as a functional unit for environmental impact and affordability analyses.

Methods: The NVS combines 7 weighted components—nutrient ratios (sodium:potassium, saturated:unsaturated fat, and carbohydrate: fiber), vitamins, minerals, protein (quality-adjusted), n–3 fatty acids, fiber, and Calories—scaled from 1 to 100, with a 25% penalty for ultraprocessed foods. It was applied to 289 commonly consumed foods in Indonesia, Bangladesh, Kenya, Nigeria, and the United States using local food composition data where available. We evaluated content validity, face validity, convergent and discriminant validity, and conducted various sensitivity analyses.

Results: The NVS identified organ meats, dark green leafy vegetables, fish, and seafood as the highest-scoring foods and soft drinks, grain-based baked sweets, instant noodles, packaged ultraprocessed snacks, and refined grains as the lowest. It showed stronger discrimination within fruits, vegetables, animal-source foods, and starchy staples than Nutri-Score or Health Star Rating (HSR). Correlations were moderate overall with Nutri-Score ($r = 0.58$) and HSR ($r = 0.63$) but weak for ultraprocessed foods ($r < 0.15$). Rankings shifted notably when using mass-based compared with energy-based references units.

Conclusions: The NVS better distinguishes foods with high nutritional value than popular existing NPS and supports more meaningful environmental impact and affordability comparisons than conventional mass-based or energy-based reference units. Although further criterion validation is needed, the NVS shows promise to guide policies and programs prioritizing nutritious foods globally.

Keywords: nutrient profiling system, Nutritional Value Score, nutrient density, food composition, noncommunicable diseases

Introduction

Nutrient deficiencies and related undernutrition (including stunting, wasting, and anemia) are widespread in low- and middle-income countries (LMICs), with as many as 9 in 10 females being deficient in ≥1 micronutrient and 1 in 2 females experiencing anemia in several countries in South Asia and sub-Saharan Africa [1,2]. Nearly 1 in 3 children aged <5 y in sub-Saharan Africa and South Asia have stunted growth, with lifelong consequences that include increased risk of infections,

Abbreviations: ALA, alpha-linolenic acid; *C*, Calories score; *CFR*, carbohydrate:fiber; DPA, docosapentaenoic acid; DIAAS, Digestible Indispensable Amino Acid Score; *F*, fiber score; *FE*, quantity of fiber per unit energy; *FM*, quantity of fiber per unit mass; HSR, Health Star Rating; LMIC, low- and middle-income countries; *M*, mineral score; *ME*, mineral density per unit energy; *MM*, mineral density per unit mass; *n3E*, *n*-3 fatty acid density per unit energy; *n3M*, *n*-3 fatty acid density per unit mass; *n3*, n–3 score; *NaKR*, sodium:potassium ratio; NDS, Nutrient Density Score; NPS, nutrient profiling systems; *NR*, nutrient ratios score; NVS, Nutritional Value Score; omega-3s, n-3 fatty acids; *P*, protein score; *pe*, quantity of protein per unit energy; *pm*, quantity of protein per unit mass; RNI, recommended nutrient intakes; *SUR*, saturated:unsaturated fatty acids ratio; *V*, vitamin score; *VE*, vitamin density per unit energy; *VM*, vitamin density per unit mass

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impaired cognitive development, reduced educational attainment, lower economic productivity, and increased risk of noncommunicable diseases [3]. The problem of undernutrition is not unique to females and children. Most males and females of all ages in LMICs do not consume enough iron, calcium, and other essential micronutrients, which compromises their health and limits their potential [4]. At the same time, noncommunicable diseases are on the rise, creating a widespread double burden of malnutrition [5]. Indeed, >80% of deaths caused by noncommunicable diseases occur in LMICs [6].

Addressing this complex nutritional landscape in LMICs and beyond requires evidence-based, fit-for-purpose tools and strategies, such as suitable nutrient profiling systems (NPS) for global application, that can be tailored to guide programmatic and policy decisions across diverse geographic settings—accounting for local nutritional and health priorities. NPS use food composition data to estimate the nutritional value or healthfulness of foods [7–9], and have typically been used to guide consumer choice, food policy, industry formulations, and investments in high-income countries. Popular implementations of NPS, including Nutri-Score in several European countries and Health Star Ratings (HSR) in Australia and New Zealand, were developed for front-of-package labeling primarily intended to reduce noncommunicable disease risk, but do not attempt to capture essential nutrient density. Others like Food Compass [9,10], and the Nutrient Rich Foods index [11], have been developed using data from high-income countries but aim to better capture risk for noncommunicable diseases *and* essential nutrient density. Food Compass [9,10] has notable strengths, including incorporating a wide range of dietary attributes reflective of healthfulness, like nutrient ratios, and validating against measures of diet quality, cardiovascular disease, and mortality [12]. The Nutrient Rich Foods index [11] has unique strengths, like excluding nutrients of limited public health relevance and offering adaptations for different uses, as well as validating against diet quality measures. However, both Food Compass and the Nutrient Rich Foods index only quantify nutritional value per calorie, which may underestimate the potential of nutritious but energy-dense foods. Neither system accounts for differences in bioavailability of key nutrients like iron, zinc, and essential amino acids [13]. Additionally, Food Compass includes some nutrients like phosphorus [14] and dietary cholesterol [15] that have limited public health relevance, while the Nutrient Rich Foods index estimates noncommunicable disease risk using nutrients to limit, rather than nutrient ratios, which evidence suggests may better predict disease risk [9].

We hypothesized that an NPS incorporating both dietary attributes predictive of undernutrition and noncommunicable disease risk, applied to locally available foods with adjustments for nutrient bioavailability and quality, would better discriminate the nutritional value of foods within and across food groups than existing systems designed primarily for high-income countries—hence making it more suitable for application to diverse contexts globally. To test this, we developed and validated the Nutritional Value Score (NVS)—a novel NPS designed to identify foods with high nutritional value relevant to public health priorities and to serve as a functional unit for future environmental impact and affordability analyses.

Methods

We developed the NVS based on health priorities to discriminate the nutritional value of foods and beverages both across and within food groups, with the primary aim of informing evidence-based policy and programming globally. We also produced a Nutrient Density Score (NDS; an independent score from the NVS) based solely on protein and the 3 essential nutrient components [vitamins, minerals, and omega-3s (n-3 fatty acids)], which can be used to identify nutrient-dense foods to be targeted in policies and programs seeking to address protein and essential nutrient deficiencies and associated undernutrition.

Nutritional Value Score

The NVS follows the latest scientific guidance on developing NPS for global use [8], food sustainability assessments [16], and affordability assessments [17]. Although NPS have historically focused on high-income countries, we developed the NVS using local foods and data (to the extent possible given data availability constraints) from countries of all incomes in 5 world regions, to ensure global relevance. The NVS aims to capture the variation in nutritional value across a range of foods and beverages (beverages included animal milks, plant-based milk alternatives, and soft drinks like cola and Gatorade). It assesses the quantity and quality of protein and essential nutrients as well as other dietary attributes that reflect protection against noncommunicable diseases. The NVS and each component score, except for the Calories score, is scaled (normalized) from 1 to 100, where 1 is the food with the lowest nutritional value and 100 is the food with the highest. The Calories score is scaled from –100 to 0, where –100 is the lowest score (highest in calorie density) and 0 is the highest score (lowest in calorie density).

We scaled the NVS across 289 unique foods in Indonesia (Southeast Asia), Bangladesh (South Asia), Kenya (East Africa), Nigeria (West Africa), and the United States (North America) to ensure representation across countries of all incomes globally (Supplementary Figure 1). The NVS approach has also been expanded to additional foods from numerous countries across 3 world regions, namely sub-Saharan Africa, South and Southeast Asia, and Latin America [18,19]. The NVS is the weighted mean of 7 normalized dietary attribute scores: vitamins (20%), minerals (20%), protein (12.5%), n–3 fatty acids (10%), fiber (7.5%), Calories (7.5%), and nutrient ratios (22.5%) (Figure 1). Ultraprocessed foods are assigned a 25% penalty before normalizing the NVS. We selected these attributes based on their health priority and data availability across diverse foods in existing food composition databases. Nevertheless, we recognize that the choice of weight and penalty for each dietary attribute is partially subjective and dependent on the perspective of the researchers.

Global diets are commonly lacking in essential vitamins, minerals, protein, essential amino acids, and n–3 fatty acids [1,4,20–24]. We established their relative weights in the NVS based on the global prevalence and severity of health consequences of inadequacy and deficiency, and on the number of nutrients included in the attribute. The vitamins and minerals attributes make up 40% of the NVS because deficiency in 1 or more of 4 essential micronutrients is prevalent in over half of

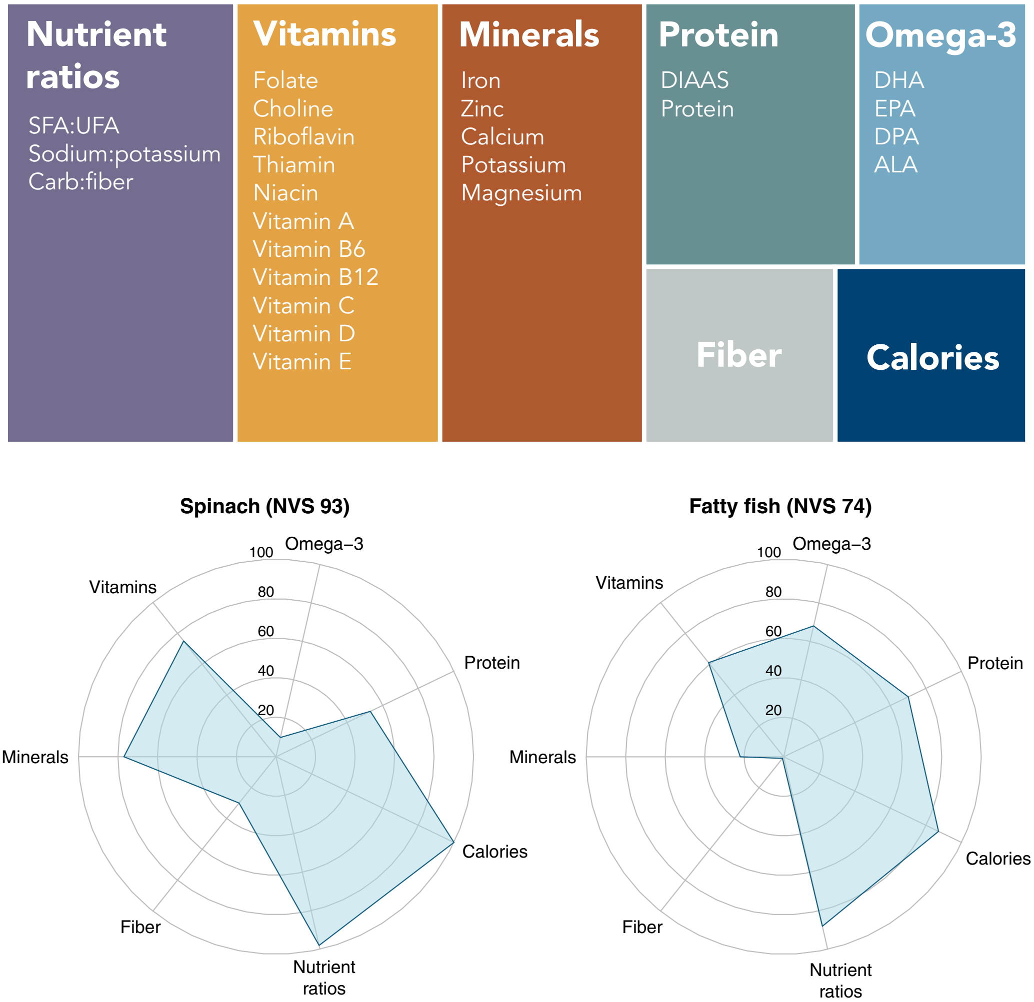

FIGURE 1. NVS components. The NVS rates foods by nutritional value. It is scaled from 1 (lowest) to 100 (highest). The area of the boxes indicates the weights of each component in the algorithm. Ultraprocessed foods are given a 25% penalty before scaling the final score. Radar plots show the component scores for 2 sample foods. The Calories score is inverted so that it can be viewed on the same scale as the other components (i.e., higher scores represent foods lower in calorie density and lower scores represent foods higher in calorie density). ALA, alpha-linolenic acid; DIAAS, Digestible Indispensable Amino Acid Score; DPA, docosapentaenoic acid; NVS, Nutritional Value Score; SFA, saturated fatty acids; UFA, unsaturated fatty acids.

preschool-aged children (iron, zinc, and vitamin A) and two-thirds of females of reproductive age (iron, zinc, and folate) globally, causing a substantial public health burden [1]. Moreover, estimated dietary inadequacies of numerous single micronutrients also show a high prevalence worldwide [4,22,23]. We weighted the protein attribute 7.5% points lower than the vitamins and minerals attributes because deficiency in essential amino acids is less prevalent but still poses a public health challenge globally [21]. We weighted the n–3 fatty acids attribute 10% points lower than vitamins and minerals attributes because, although approximately two-thirds of adults are estimated to have low intake of DHA and EPA and one-fifth are estimated to have inadequate intake of alpha-linolenic acid (ALA) [20], the n-3 fatty acids attribute includes just 1 essential nutrient whereas the vitamins and minerals attributes each include multiple essential nutrients.

We weighted the fiber attribute 12.5% points lower than the vitamins and minerals attributes. This is because, although inadequate fiber intake is common worldwide [25], fiber is not an essential nutrient. Also, like the n-3 fatty acids attribute, fiber is the only component within the attribute. We weighted the Calories attribute the same as the fiber attribute and the individual nutrient ratios included in the nutrient ratio score to be consistent. We weighted the nutrient ratios attribute 2.5% points higher than the vitamins and minerals attributes, because nutrient ratios are important for assessing risk of noncommunicable diseases, which are widespread globally and increasing [9,26]. We penalized ultraprocessed foods, defined according to the Nova system, by 25% given their prominent association with noncommunicable diseases [27]. Although the specific 25% penalty is not derived from a single study or data point, it represents a considered estimate of the impact of ultraprocessing based on current evidence [27]. This moderate penalty meaningfully impacts food rankings without dominating the score (as demonstrated in sensitivity analyses) and can be readily adjusted as more research becomes available on the health effects of ultraprocessed foods and depending on contextual factors (e.g. the public health burden of obesity, noncommunicable diseases, and consumption levels of ultraprocessed foods in each country). Each dietary attribute is described in further detail below.

Vitamins

The vitamin score (*V*) reflects the quantity and quality of 11 vitamins of public health priority: folate, choline, riboflavin, thiamin, niacin, and vitamins A, B-6, B-12, C, D, and E. Low supply, low intake, or deficiency of these vitamins is common worldwide [1,4,22–24]. *V* is the average of 2 subscores—*VE* and *VM*—each normalized between 1 and 100. *VE* reflects the vitamin density per unit energy. *VM* reflects the vitamin density per unit mass. Scoring foods per unit energy *and* mass ensures foods low in energy or mass are not unduly favored in the overall score. *VE* is calculated as follows:

$$VE_i = \frac{1}{A}\sum_{a \in A} \min\left\{ve_{a,i},\ 1\right\}$$

where *ve* is the proportion of recommended nutrient intakes (RNIs) [28,29], for each of the 11 vitamins (*A*) provided in 300 Calories of each food (*i*). Each vitamin's contribution to *VE* per 300 Calories was capped at the RNI to prevent foods very high in 1 vitamin from inflating the score. Although the chosen reference amount is subjective (as for all NPS), 300 Calories corresponds to about 13% of average energy requirements for moderately active individuals [29], which represents a relatively plausible amount of energy to obtain from a single food in 1 d (except for low-calorie foods).

VM is calculated the same as *VE* but per 231 g of each food. This quantity was calculated by dividing 300 Calories by 1.3 Calories/g (the mean energy density of a minimally processed plant-based, low-fat diet and an animal-based, ketogenic diet) [30]. Foods with ≥4 added vitamins were assigned a 25% penalty, to prevent heavily fortified foods from having an overly inflated vitamin score. To assess whether a processed or ultraprocessed food was fortified with ≥4 vitamins, in cases where it was not explicitly labeled as "fortified" or "enriched" in the food composition databases used for this analysis, we systematically compared its vitamin values to those of the corresponding unenriched unprocessed or minimally processed ingredients.

Minerals

The mineral score (*M*) reflects the quantity and quality of 5 protective minerals of public health priority: iron, zinc, calcium, potassium, and magnesium. Low supply, low intake, or deficiency of these minerals is common worldwide [1,4,22–24]. *M* is the average of 2 sub-scores—*ME* and *MM*—each normalized between 1 and 100. *ME* reflects the mineral density per unit energy. *MM* reflects the mineral density per unit mass. *ME* is calculated as follows:

$$ME_i = \frac{1}{A}\sum_{a \in A} \min\left\{me_{a,i},\ 1\right\}$$

where *me* is the proportion of RNIs [28,29] for each of the 5 minerals (*A*) provided in 300 Calories of each food (*i*). Each mineral's contribution to *ME* per 300 Calories was capped at the RNI to prevent foods very high in 1 mineral from inflating the score. Iron and zinc contents were adjusted for bioavailability following Beal and Ortenzi [31].

MM is calculated the same as *ME* but per 231 g of each food. This quantity was calculated by dividing 300 Calories by 1.3 Calories/g (the mean energy density of a minimally processed plant-based, low-fat diet and an animal-based, ketogenic diet) [30]. Foods with ≥2 added minerals were assigned a 25% penalty to prevent heavily fortified foods from having an overly inflated mineral score. To assess whether a processed or ultraprocessed food was fortified with ≥2 minerals, in cases where it was not explicitly labeled as "fortified" or "enriched" in the food composition databases used for this analysis, we systematically compared its mineral values to those of the corresponding unenriched unprocessed or minimally processed ingredients.

Protein

The protein score (*P*) reflects the quantity and quality of protein. *P* is the average of 2 subscores—*p* and Digestible Indispensable Amino Acids Score (*DIAAS)*—each normalized between 1 and 100. *p* is the average of 2 subscores—*pe* and *pm*—each normalized between 1 and 100. *pe* is the quantity of protein in 300 Calories of each food. *pm* is the quantity of protein in 231 g of each food. *DIAAS* is the untruncated DIAAS.

n–3 fatty acids

The n–3 score (*n3*) reflects the quantity and quality of n–3 fatty acids. *n3* is the average of 2 subscores—*n3E* and *n3M*—each normalized between 1 and 100. *n3E* reflects the *n*–3 fatty acid density per unit energy. *n3M* reflects the n–3 fatty acid density per unit mass. *n3E* is calculated as follows:

$$n3E_i = \max(DHA_i + EPA_i + DPA_i, ALA_i)$$

where *DHA* + *EPA* + DPA and *ALA* indicate the proportion of RNIs of long chain (250 mg) and short chain (1240 mg) n–3 fatty acids, respectively, provided in 300 Calories of each food (*i*) [32]. *n3M* is calculated the same as *n3E* but per 231 g of each food.

Fiber

The fiber score (*F*) reflects the quantity of fiber. *F* is the average of 2 subscores—*FE* and *FM*—each normalized between 1 and 100. *FE* is the quantity of fiber in 300 Calories of each food. *FM* is the quantity of fiber in 231 g of each food.

Calories

The Calories score (*C*) reflects the density of Calories. *C* is the energy:mass ratio, normalized between –100 (highest calorie density) and 0 (lowest calorie density). We assigned zero values to foods containing <1.3 Calories/g (the mean energy density of a minimally processed plant-based, low-fat diet and an animal-based, ketogenic diet) [30], to avoid penalizing foods with moderate calorie density.

Nutrient ratios

The nutrient ratios score (*NR*) reflects the increased risk for noncommunicable diseases from consuming foods high in carbohydrates and low in fiber, high in sodium and low in potassium, and high in saturated fat and low in unsaturated fat [9, 26]. *NR* is the average of 3 negative subscores each normalized between –100 and 0: *CFR*, *NaKR*, and *SUR*. *NR* is normalized between 1 and 100. *CFR* is the carbohydrate:fiber ratio. We assigned zero *CFR* values (best score) to foods with <10% of Calories from carbohydrates to avoid penalizing foods containing small quantities of carbohydrates; unsweetened dairy products; and foods with ≥20% of Calories from protein, since naturally occurring carbohydrates in these foods are not typically associated with health risks [33]. *NaKR* is the sodium:potassium ratio. We assigned zero *NaKR* values to foods containing <0.9 mg sodium/Calorie, in alignment with the World Health Organization's recommendations for adults to limit daily sodium intake to <2000 mg (assuming an average energy requirement of 2227 kcal for moderately active individuals [29]). *SUR* is the saturated:unsaturated fatty acids ratio. We assigned zero *SUR* values to foods containing <10% of energy from fat, to avoid penalizing foods containing small quantities of fat overall for having minimal quantities of saturated fats. For all nutrient ratios, we replaced infinite values with the worst non-infinite values in the dataset, to avoid mathematical errors and ensure that extreme outliers did not disproportionately skew the analysis, while still preserving the relative position of foods with infinite values as the least favorable within the dataset. For *NaKR* and *SUR*, we used a log transformation to account for their skewed distributions.

Liquid dairy and dried foods

For unsweetened milk, sour milk, fermented milk, and semiliquid yogurts and cheese (such as cottage cheese), including plant-based alternatives, we based the scores for *V*, *M*, *P*, *n3*, and *F* exclusively on *VE*, *ME*, *pe*, *n3E*, and *FE*, respectively, since they are low in Calories and their mass is not a barrier to consumption as it is with solid foods. We scaled dried foods typically consumed rehydrated (e.g. milk powder) to the same energy density as their fresh food counterparts, so that they would be analyzed in the form typically consumed.

Nutrient Density Score

The NDS reflects the overall quantity and quality of protein and essential nutrients of public health priority. The NDS is normalized between 1 and 100 where 1 represents the food with the lowest nutrient density and 100 represents the food with the highest nutrient density. The NDS is the weighted average of 4 normalized dietary attribute scores: vitamins (35%), minerals (35%), protein (20%), and n–3 fatty acids (10%). We weighted vitamins and minerals equally and highest because micronutrient deficiencies are the most prevalent and severe form of nutrient inadequacy globally [1,4]; protein lower because essential amino acid deficiency is less prevalent but still a public health challenge [17]; and n–3 fatty acids lowest because although inadequate intakes are common worldwide [20], this attribute only includes a single nutrient.

Food composition data

For the NVS analysis, we built a master food composition database for foods from Indonesia, Bangladesh, Kenya, Nigeria, and the United States, with values for Calories carbohydrates, fiber, protein, mono and polyunsaturated fatty acids, saturated fatty acids, 11 vitamins, 6 minerals, short and long chain n–3 fatty acids, phytate, and the DIAAS. We also developed a modified version of the master database, including only Indonesian foods and ultraprocessed foods from the United States, with values for 5 additional components required to apply the Nutri-Score and HSR algorithms (more details available in the Supplementary Material).

Values for most foods were obtained from USDA databases [34], complemented by national (i.e., Indonesia, Bangladesh, Kenya, and Nigeria) and regional (i.e., West Africa) food composition tables for local foods which were not available in USDA databases [35]. The choice to primarily rely on USDA data was due to the limited set of foods and nutrients included in national or regional food composition tables, which was insufficient to implement the NVS algorithm. For the specific local foods that we extracted from national or regional food composition tables, we used food subgroup average values from USDA databases to fill in the gaps for any nutrients not included in national or regional food composition tables. Values for the DIAAS were obtained from the literature, by prioritizing studies conducted in humans, followed by those conducted in pigs and, as a third option, rats, and by preferring average over single values when available. Values for phytate were derived from the Food and Agriculture Organization's Global Food Composition Database for Phytate [36].

Our analysis included 258 unique unprocessed, minimally processed, and processed foods recommended in dietary guidelines globally [37], as well as 31 unique ultraprocessed foods [38]. Ultraprocessed foods were identified based on the Nova classification system [38], by systematically examining food descriptions and, where available, ingredient lists, and comparing them to their minimally processed or processed food counterparts. For Indonesia, Bangladesh, and Kenya, we included unprocessed, minimally processed, and processed sentinel foods listed in the respective country-adapted Diet Quality Questionnaires (dietquality.org). For Nigeria, we included unprocessed, minimally processed, and processed foods from national retail food price lists made available by the National Bureau of Statistics (nigerianstat.gov.ng). Including foods from country-adapted Diet Quality Questionnaires or national retail food price lists ensured the relevance of our analysis to the local contexts, by focusing on locally available, commonly consumed foods. With regards to the United States, we selected a variety of ultraprocessed foods representative of different categories within this broad food group (e.g. soft drinks, baked grain-based sweets, and ultraprocessed meat). This helped fill gaps in ultraprocessed food groups in the Diet Quality Questionnaire that are linked with global dietary recommendations to prevent noncommunicable diseases. We chose ultraprocessed foods from the United States as opposed to Indonesia, Bangladesh, Kenya, or Nigeria, because these foods are rarely available in national or regional food composition tables, and, when they are, they contain numerous missing values.

We compiled data on the composition of foods as they are usually consumed (i.e., raw, cooked, or both) within the respective country context. Where applicable and where data were available, nutrient values for multiple cooking methods for the same food were averaged. In addition, for meat, nutrient densities for various cuts, degrees of fat, and portions of the same animal were averaged. With regards to aggregate foods (e.g. fish, rice, and sausage), food composition data from different species or varieties were collected and averaged (e.g. fish species popular in each country, different varieties of rice, and sausages of diverse animal origin). Furthermore, we separated fatty from lean fish, marine from freshwater fish, full-fat from low-fat dairy (milk, cheese, and yogurt), moderately processed from ultraprocessed meat (defined according to the Nova classification system [38]), regular from low-fat processed meat, and whole grains from refined grains, because of the significant differences in food composition and nutritional value between these food subgroups.

Missing values for individual foods were replaced with the corresponding values for close proxies, if available, or with average values for all foods within the respective Diet Quality Questionnaire question. For example, if the vitamin E density of water spinach (question 6.1 in the Diet Quality Questionnaire for Indonesia) was missing, the average value for all vegetables under question 6.1 would be used, assuming that foods belonging to the same Diet Quality Questionnaire question have comparable nutrient density. For Nigerian and United States foods which were not directly sourced from Diet Quality Questionnaires, these were first matched to the corresponding questions in the respective country-adapted Diet Quality Questionnaires before applying the above-mentioned approach for handling missing values. This approach allowed us to fill all data gaps except for ALA, whose value was only available for a limited set of foods in USDA databases, and for which we sometimes had to rely on available literature. For more details on the food composition data, refer to the Supplementary Material.

Dietary reference intakes

For vitamins and minerals, we used harmonized nutrient reference values for global application, which recommend a mix of values from the European Food Safety Authority [29] and the Institute of Medicine [28], depending on the micronutrient (Supplementary Tables 1 and 2) [39]. For n-3 fatty acids, we used European Food Safety Authority RNIs [29].

Sensitivity analyses

We conducted 6 sensitivity analyses. First, we capped vitamin and mineral contents at 50% and 200% of the RNI. Second, we shifted the weights of dietary attributes toward protection against noncommunicable disease: *V* (10%), *M* (10%), *P* (10%), *n3* (12.5%), *F* (15%), *C* (15%), and *NR* (27.5%), with a 35% penalty for ultraprocessed foods; and nutrient density: *V* (30%), *M* (30%), *P* (20%), *n3* (10%), *F* (2.5%), *C* (2.5%), *NR* (5%), with a 15% penalty for ultraprocessed foods. Third, we winsorized the NVS by truncating outliers at the 5th and 95th percentiles. Fourth, we assigned no penalties to the vitamin and mineral scores for fortified foods. Fifth, we assigned no penalty to ultraprocessed foods. Last, we calculated the NVS when using mass or energy as the sole reference unit.

Validation

We confirmed content validity of the NVS algorithm by aligning its components and weights with public health priorities in the scientific literature, expert peer feedback from 3 nutrition scientists at the Global Alliance for Improved Nutrition, and various sensitivity analyses. We tested face validity by applying the NVS algorithm to 289 unique foods in Indonesia, Bangladesh, Kenya, Nigeria, and the United States and analyzing each component score and final NVS across foods individually and by 6 broad food groups: 33 fruits; 60 vegetables; 29 legumes, nuts, and seeds; 83 animal-source foods; 53 starchy staples; and 31 ultraprocessed foods. We also confirmed the face validity of the NVS for food subgroups in the Diet Quality Questionnaire and a few additional food groups. We tested convergent and discriminant validity by comparing the NVS with Nutri-Score and HSR for foods overall and by broad food groups and food subgroups (including ultraprocessed foods), separately. Nutri-Score and HSR were chosen because they are among the most prominent NPS worldwide for policy, industry, and programmatic applications, and are being considered for global and regional adoption.

Statistical analyses

We used Spearman rank correlations to assess convergent and discriminant validity by comparing the NVS with Nutri-Score and HSR overall and by broad food group (e.g. vegetables, fruits). Spearman correlations were chosen because they do not assume normality and are robust to outliers. All other analyses were descriptive, including comparisons of component scores and NVS distributions across food groups, as well as comparisons of NVS, Nutri-Score, and HSR rankings at the food subgroup level (e.g. dark green leafy vegetables, citrus fruits). All analyses were conducted using R version 4.4.1 (R Core Team).

Results

Nutritional Value Scores

The NVS can be used to compare the nutritional value of food groups and single foods, and it can be calculated for meals and total diets. Aggregating across common food groups, the highest-scoring food groups (mean NVS >75) are dark green leafy vegetables and organ meat (Figure 2). Moderately high-scoring food groups (mean NVS 50–75) include fish and seafood, unprocessed red meat, other vegetables, eggs, legumes, poultry, vitamin A-rich fruits and vegetables, moderately processed meat, milk, yogurt, and nuts and seeds (Figure 2). Moderately low scoring food groups (mean NVS 25–49) include refined grains, egg substitute, ultraprocessed meat, cheese, sweetened milk or alternatives, whole grains, fortified whole grain breakfast cereals; white roots, tubers, and plantains; other fruits, and citrus (Figure 2). The lowest scoring food groups (mean NVS <25) include soft drinks, baked grain-based sweets, instant noodles, packaged ultraprocessed salty snacks, and other sweets (Figure 2).

When looking at single foods, the highest scores (NVS >75) are seen for dried okra, dried fish and shellfish, spinach and other dark green leafy vegetables, chicken and beef organs, and sardines and other small fish (Supplementary Table 3, Figure 3). Moderately high-scoring foods (NVS 50–75) include a larger range of foods like unsweetened cow milk and soymilk, zucchini, bivalves, crustaceans, beef, sunflower seeds, lentils, pork, carrots, chicken, tofu, eggs, passion fruit, guava, orange-fleshed sweet potato, and almonds, among others (Supplementary Table 3, Figure 3). Moderately low scoring foods (NVS 25–49) include hot dogs, sweet potato chips, chocolate milk, watermelon, eggplant, brown rice, and Cheerios, among others (Supplementary Table 3, Figure 3). The lowest scores (NVS <25) belong to Gatorade, cola, congee, several sweet and savory ultraprocessed foods, instant noodles, coconut, and white rice and products (Supplementary Table 3, Figure 3).

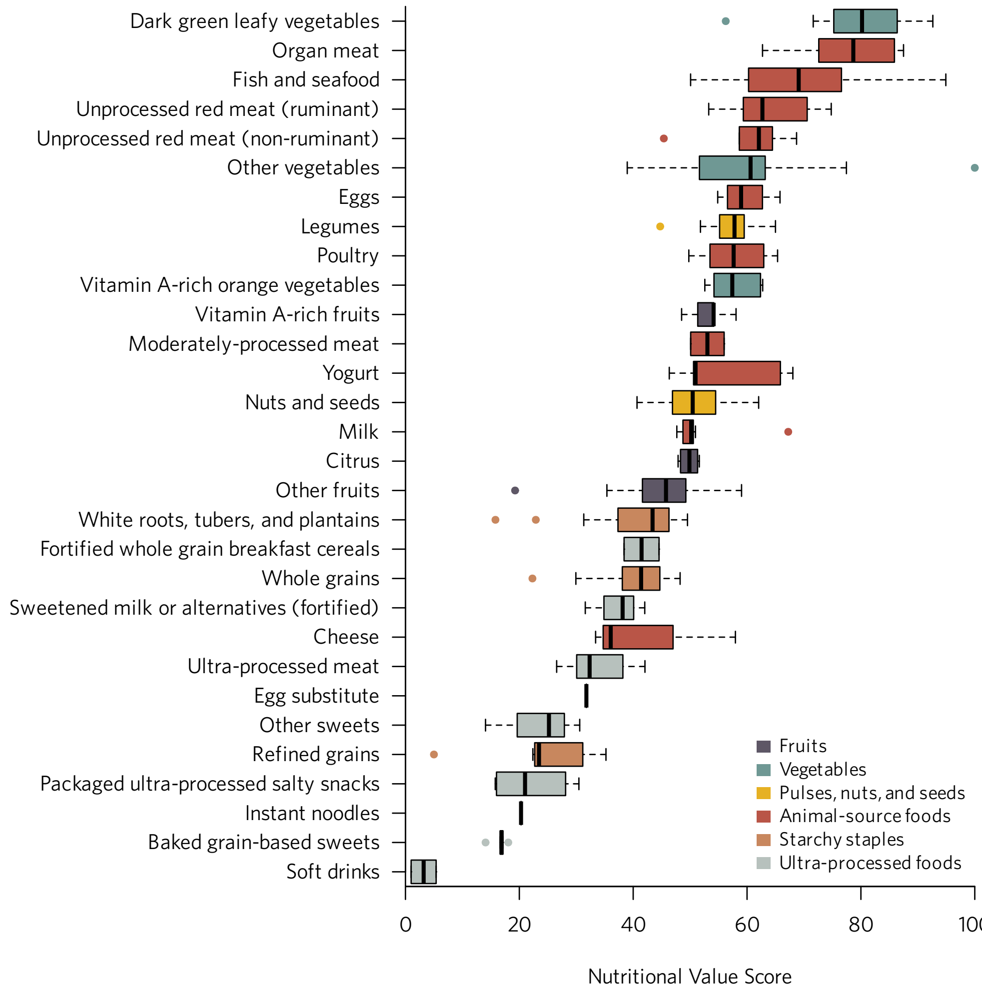

FIGURE 2. Nutritional Value Scores for 289 unique foods in Indonesia, Bangladesh, Kenya, Nigeria, and the United States categorized into common food groups. Standard boxplots are shown, with the center line representing the median score, the shaded bars representing the interquartile ranges (25th–75th percentiles), the error bars representing 1.5×IQR, and the small points representing outliers.

Component nutritional scores

No food scores high in all components. For example, spinach, the third highest-scoring food, has high scores for most components yet an n–3 score of just 10 (Figure 1, Supplementary Table 3). Foods with the highest vitamin scores are organ meats and dark green leafy vegetables like spinach and moringa leaves, whereas foods with the lowest vitamin scores include soft drinks, certain starchy staples like white rice noodles and refined wheat pasta, fruits like coconut and watermelon, and certain legumes like oncom and tofu (Supplementary Table 3). Mineral scores are highest for dried vegetables (e.g. dried okra), dark green leafy vegetables, dried fish and shellfish, and certain seeds (e.g. sunflower seeds) and are lowest for soft drinks, instant noodles, certain starchy staples like white rice noodles and white rice, fruits like watermelon and apple, and certain vegetables like tree fern and eggplant (Supplementary Table 3). Dried fish and shellfish, nonfat Greek yogurt, and lean meats like boar and deer have the highest protein scores followed by other animal-source foods and, to a lesser extent, soy products like tempeh, whereas soft drinks and starchy staples like fufu and cassava have the lowest protein scores followed by other ultraprocessed foods (Supplementary Table 3). Lastly, fatty fish and shellfish are the only high-scoring foods in terms of n-3 fatty acids content. Foods with the highest overall NDS are fish and shellfish (especially dried varieties), dried okra, organ meats, dark green leafy vegetables, and deer, whereas the foods with the lowest NDS are primarily soft drinks, starchy staples, other ultraprocessed foods, and fruits like watermelon and apple (Supplementary Table 3).

For fiber, the foods with the top scores are nonstarchy vegetables (especially dried varieties), certain grains (e.g. corn), fruit (e.g. passion fruit), and legumes, nuts, and seeds (e.g. pumpkin seeds), whereas the lowest fiber scores are attributed to soft drinks, animal-source foods, plant-based milk alternatives, refined starchy staple foods, other ultraprocessed foods, and certain fruits (e.g. watermelon) (Supplementary Table 3). For Calories, the foods with the least desirable scores are nuts and seeds and ultraprocessed foods, whereas most other foods received the top score since they fall below the calorie density cutoff of 1.3 Calories/g (Supplementary Table 3). Similarly, most foods score highly on nutrient ratios because they are mostly foods recommended in dietary guidelines (Supplementary Table 3). The lowest scoring food is congee followed by ultraprocessed foods and select other foods including full-fat cheese, coconut, dried beef, and millet porridge (Supplementary Table 3).

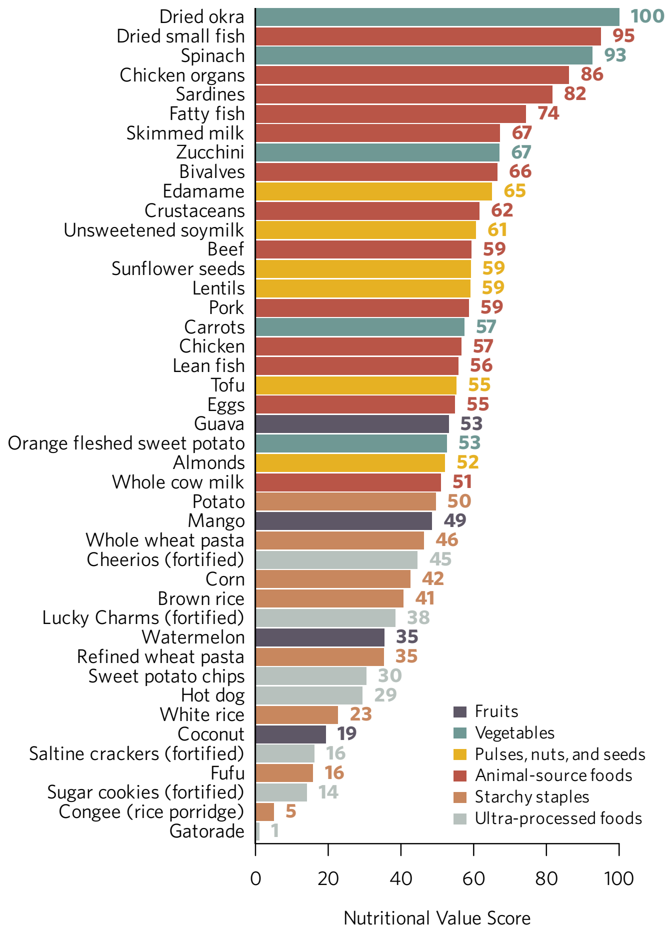

FIGURE 3. Nutritional Value Scores for common foods in Indonesia, Bangladesh, Kenya, Nigeria, and the United States.

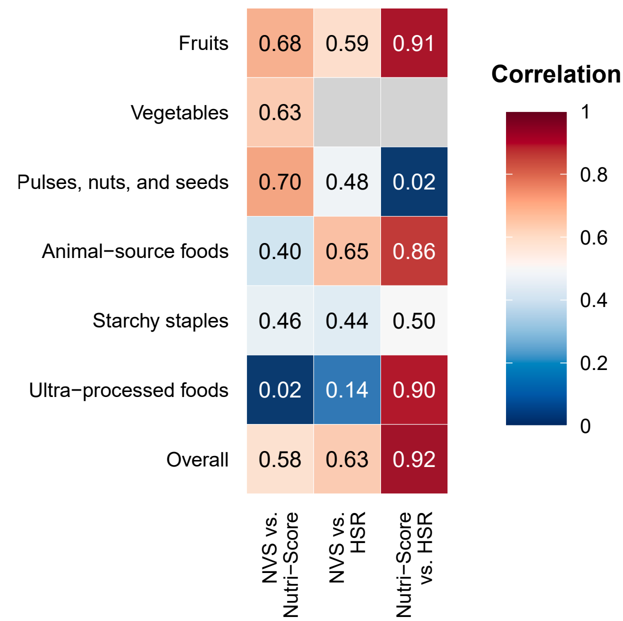

FIGURE 4. Correlations between various nutrient profiling systems for 133 unique foods in Indonesia and the United States. Nutri-Score and HSR first generate a numerical score, which is then used to classify a product into a category. These numerical scores were used to assess Spearman correlations (values shown) between the different nutrient profiling systems. For Nutri-Score and HSR, lower numerical scores are considered healthier, and thus correlations with the NVS were evaluated for the inverse of their scores. Gray boxes indicate there was not enough variation in the data to complete the analysis (e.g. all vegetables were assigned the same numerical score when applying the HSR algorithm). HSR, Health Star Rating; NVS, Nutritional Value Score.

Comparison with existing NPS

A subset of the 289 unique foods ($n = 133$), representing all analyzed food (sub-)groups, contained information needed to calculate Nutri-Score and HSR. We compared the NVS results for these 133 unique foods in Indonesia and the United States with Nutri-Score and its underlying points and HSR and its underlying scores, using the latest publicly available versions of the Nutri-Score and HSR algorithms. Spearman correlations indicate moderate overall correlation between the NVS and Nutri-Score (0.58) and HSR (0.63) (Figure 4). There was a stronger correlation between the NVS and HSR for animal-source foods (0.65) than between the NVS and Nutri-Score (0.40) (Figure 4). There was a stronger correlation between the NVS and Nutri-Score for legumes, nuts, and seeds (0.70) than for HSR (0.48) (Figure 4), partly because unenriched unsweetened soymilk (NVS 61) receives a rating of just 1 star on HSR, whereas it gets a B rating on Nutri-Score. The correlation between the NVS with both Nutri-Score and HSR was relatively weak for starchy staples (<0.5) and very weak for ultraprocessed foods (<0.15) (Figure 4). There was a stronger correlation between Nutri-Score and HSR overall (0.92) (Figure 4).

Animal-source foods, especially organ meats, tend to perform better on the NVS compared with Nutri-Score, whereas starchy staples (especially refined grains), fruit; legumes, nuts, and seeds; and vegetables other than dark leafy greens tend to perform better on Nutri-Score (Figure 5). There is little variation in the Nutri-Score ratings for vegetables, whereas the NVS varies considerably (Supplementary Figure 2; Figures 5 and 6). For HSR, there is almost no variation in the scores for fruits and vegetables, whereas NVS shows large variation (Supplemental Figures 3–7). Across all foods overall, there is large variation in the NVS within each Nutri-Score rating (especially for foods receiving an A rating) and HSR classification (especially for foods receiving a 5-star rating) (Figure 6, Supplementary Figure 7). All starchy staples receive a Nutri-Score of C or higher and an HSR of 3.5 or higher, whereas the NVS assigns refined grains an average NVS of about 20, positioning them among the lowest scoring food groups (Figure 5). The largest variation in both Nutri-Score points and HSR scores occurs in foods with an NVS of 21–40 (Supplementary Figures 8 and 9).

The NVS as a functional unit

Environmental life cycle analyses typically assess the environmental impacts of foods in terms of kgs or Calories. However, such practices fail to account for variation in nutritional value across and within food groups. Within vegetables, for example, eggplant (NVS 39) has a lower nutritional value than spinach (NVS 93) (Supplementary Table 3)—yet a typical environmental impact assessment would equate 1 kg of eggplant to 1 kg of spinach. Comparing foods in terms of Calories also inadequately accounts for nutritional differences. Within fruits, for example, watermelon (NVS 35) has a lower nutritional value than guava (NVS 53) (Figure 3, Supplementary Table 3)—yet a typical

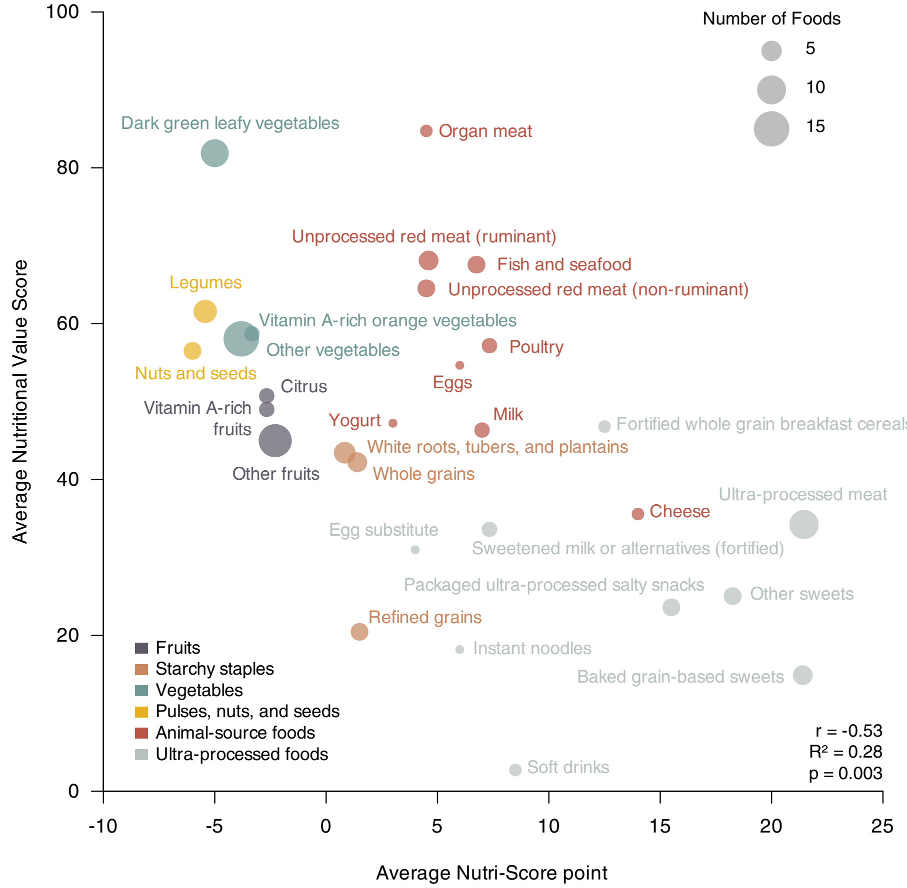

FIGURE 5. Relationship between average Nutri-Score point and Nutritional Value Score for 133 unique foods in Indonesia and the United States categorized into common food groups. Nutri-Score points range from –15 (best) to 40 (worst). Correlations (r), R^2, and the associated *P*-value are calculated based on the average bubble food group scores.

environmental impact assessment would equate 1000 Calories of watermelon to 1000 Calories of guava.

The NVS offers a more nutritionally appropriate way to assess environmental impacts of foods by measuring the nutritional value produced and standardizing it for comparisons within and across food groups. To illustrate this across food groups, just 243 g of dried small fish is needed for a NVS of 100 whereas 568 g of brown rice is needed to achieve the same NVS (Supplementary Figure 10). With respect to comparisons within food groups, it is also more appropriate to compare guava and watermelon using a fixed NVS rather than a fixed number of Calories. For example, just 565 Calories of guava is needed for an NVS of 100, whereas 848 Calories of watermelon is needed to achieve the same NVS (Supplementary Figure 11).

The NVS can be similarly used in price and affordability analyses, which face the same challenges as environmental impact assessments with nutritionally insensitive functional units based on mass or dietary energy.

Sensitivity analyses

Overall, the sensitivity analyses revealed that the NVS is robust to many changes in its parameters and weighting schemes, but certain food groups are more sensitive than others. Capping vitamin and mineral levels at different proportions of the RNIs had minor effects (Supplementary Figures 12–15), whereas shifting the focus to noncommunicable diseases or nutrient density caused notable changes, particularly for fruits, vegetables, and ultraprocessed foods (Supplementary Figures 16–19). Winsorizing the NVS impacted food groups differently, lowering scores for ultraprocessed foods, starchy staple foods, and fruits, whereas increasing scores for dark green leafy vegetables, organ meat, and fish and seafood (Supplementary Figures 20 and 21). Removing penalties for fortification or ultraprocessing primarily affected those specific food categories (Supplementary Figures 22–25). The choice of reference unit (mass or energy) significantly impacted the NVS, with mass favoring Calorie-dense foods and energy favoring low-Calorie options (Supplementary Figures 26–29). More details of the sensitivity analyses are available in the Supplemental Material.

Discussion

We developed the NVS to address the need for an NPS that captures locally available foods, nutrient bioavailability, and the dual burden of undernutrition and noncommunicable diseases—hence making it suitable for application in global settings, while also serving as a functional unit for environmental impact and affordability analyses. The NVS effectively identified

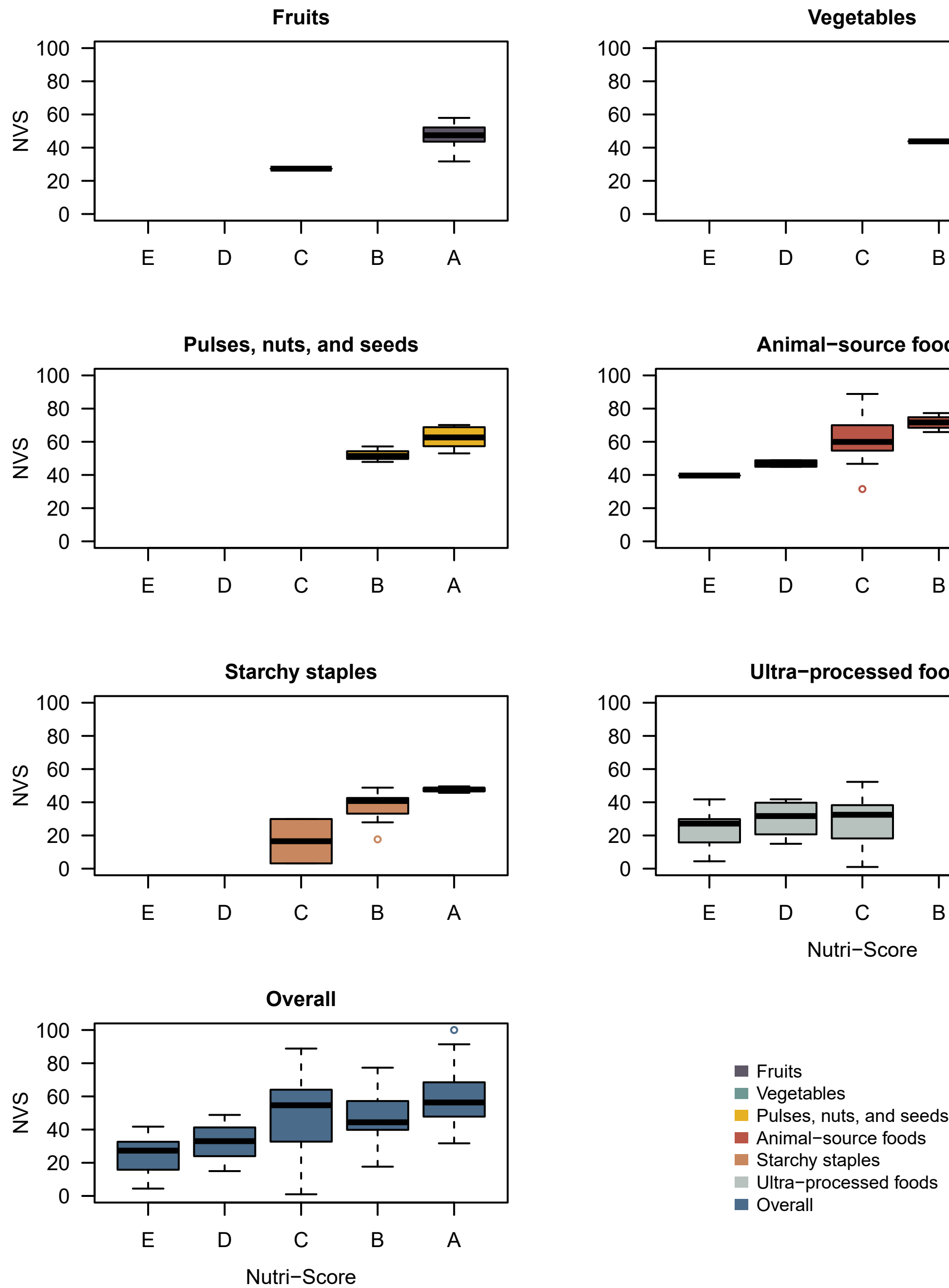

FIGURE 6. NVS according to Nutri-Score category for 133 unique foods in Indonesia and the United States. Standard boxplots are shown, with the center line representing the median score, the shaded bars representing the IQR (25th–75th percentiles), the error bars representing 1.5× the IQR, and the small circles representing outliers. Nutri-Score ranges from category E (least healthy) to category A (healthiest). NVS, Nutritional Value Score.

food groups with high nutritional value, including organ meats, dark green leafy vegetables, and fish and seafood, from food groups with lower nutritional value, like refined grains and various ultraprocessed food groups, demonstrating high discriminatory power across food groups. In contrast, Nutri-Score assigned all organ meats and fish and seafood products a C rating yet assigned most refined grains a B rating. The NVS also provided more discriminatory power *within* broad food groups. For example, all fruits and vegetables except for coconut and cauliflower received A ratings according to Nutri-Score and 5 stars according to HSR; yet the NVS rated fruits and vegetables with higher nutritional value like guava and spinach much higher than fruits and vegetables with lower nutritional value, like watermelon and eggplant. Similarly, Food Compass 2.0 gave watermelon one of its top scores—comparable to spinach [10]—failing to recognize watermelon's much lower nutritional value. HSRs overall were more correlated with the NVS than Nutri-Score, especially for animal-source foods, scoring organ meats, lean meats, and fish and seafood ≥4 stars. However, HSR also assigned refined grains ≥3.5 stars.

The greater discriminatory power of the NVS compared with Nutri-Score and HSR to identify less nutritious starchy staples like refined grains and the most nutritious fruits, vegetables, and animal-source foods makes it suitable for guiding policies and programs in LMICs facing a large burden of undernutrition. The NVS can also be further tailored to the nutritional needs of specific populations like females and young children and for specific regions [18,19]. For example, the weights of the dietary attributes can be modified to reflect the unique nutritional situation of a demographic group in a particular region, based on a review of the relative burden of various forms of dietary inadequacies and malnutrition [18,19]. The NVS complements food-based dietary guidelines because it discriminates the nutritional value of foods within commonly recommended food groups: fruits; vegetables; legumes, nuts, and seeds; animal-source foods; and starchy staples [37]. Although whole grains are an important component of healthy and sustainable diets due to their role as a primary source of dietary energy and fiber, their moderate NVS reflects their lower density of essential nutrients relative to foods like dark green leafy vegetables, fish, and organ meats—a distinction that is relevant for policies and programs aiming to address micronutrient deficiencies but that should be interpreted alongside food-based dietary guidelines, which recommend whole grains in appropriate amounts as a staple food.

Policies and programs that promote broad food groups like fruits, vegetables, and starchy staples are not enough, given the large burden of malnutrition and the dietary gaps compared with recommended diets. Targeting the most nutritious items within these food groups can have a greater impact on nutrient adequacy, diet quality, and related health outcomes, given the wide range in nutritional value of foods within these food groups. We are continuing to expand the application of the NVS to more foods and LMICs to enable further uptake by program implementers and policymakers [18,19].

The NVS is also designed for use as a functional unit in life cycle assessments to estimate environmental impacts per unit of nutritional value [40,41]. Identifying better options for such assessments is essential, as current practices vary widely [16], with no scientific consensus [42], and results tend to be unit dependent [43]. For example, a landmark global environmental impact meta-analysis used functional units of mass, energy, and total protein content [44]. A more recent study [45] used these data along with updated environmental data on aquatic foods [46] and nutritional quality as assessed by the NPS, Nutri-Score. Other researchers have used nutritional functional units based on nutrient density, for example, as assessed by variations of the Nutrient Rich Foods index [47], or by priority micronutrient value [48]. The NVS, complemented by local food, nutrition, and environmental impact data, where available, can be used to compare the environmental impact of foods across or within food groups. Assessing environmental impacts per fixed NVS using local foods and food composition data (where available) places foods on nutritionally equivalent footing, improving on prior metrics by incorporating contextually appropriate foods as well as aspects of priority nutrient density and protection against noncommunicable diseases [40]. Food-based dietary guidelines could include the resulting insights to encourage consumption of context-appropriate, sustainable, healthy diets [40].

Although not applied in the current manuscript or the scientific literature, the NVS is also designed for use in future food affordability assessments. Affordability of single foods has been assessed per unit energy [49], priority micronutrient value [50], and by the Nutrient Rich Foods index [17,51]. As with life cycle assessments, the NVS provides a more holistic way to standardize foods by nutritional value for food affordability assessments. Application of the NVS in food affordability assessments would provide insights to aid social protection programs in identifying the most affordable food sources of nutrition. Demand creation programs could focus on increasing consumer demand for the most affordable nutritious foods; at the same time, policies could help reduce the price of unaffordable nutritious foods, for example, by providing agricultural incentives, limiting the role of intermediaries in supply chains, improving infrastructure, and taking measures to counterbalance inflation [52].

To determine initial validity and robustness of the NVS, we assessed content validity, face validity, and convergent and discriminant validity and conducted various sensitivity analyses. We tested content validity of the NVS algorithm through the inclusion of dietary attributes of public health priority, comprising essential nutrients of public health concern [1,20–23] and dietary factors that indicate protection against noncommunicable diseases [9,25–27]. We tested face validity by applying the NVS algorithm across recommended local foods and ultraprocessed foods available in Indonesia, Bangladesh, Kenya, Nigeria, and the United States, disparate countries in different geographies with a high burden of malnutrition. We tested convergent and discriminant validity by comparing the NVS with Nutri-Score and HSR, two prominent NPS developed in high-income countries which are being considered for global use, including in LMICs.

We conducted sensitivity analyses of different micronutrient capping, component weights, winsorizing, removing penalties for fortified nutrients and ultraprocessed foods, and different reference units to test the robustness of the NVS to various assumptions and parameters. The large impact of reference unit choice highlights how critical it is to incorporate both mass and energy in nutrient profiling calculations, a feature that is currently unique to the NVS. If mass were the sole reference unit, low-Calorie foods would be unfairly penalized; if energy was the sole reference unit, high-Calorie foods would be unfairly penalized. Using both reference units is particularly important in LMICs facing a large double burden of malnutrition, where both low-Calorie and high-Calorie nutrient-dense foods are needed. The large impact of shifting the weights toward noncommunicable diseases or undernutrition highlights the importance of tailoring NPS to the specific nutritional challenges and priorities of the population being considered. We broadly targeted the overall population in LMICs using data from diverse countries in Africa and Asia; further tailoring based on the nutritional priorities of specific populations and regions could allow for even greater impact by addressing context-specific nutritional challenges, which vary by geography and demographics [18,19].

Future research could test the NVS for criterion validity [53], in diverse contexts, including correlating the NVS with essential nutrient biomarkers, anemia, stunting, noncommunicable disease markers, and mortality. Validation using observational studies, however, is limited due to confounding and various forms of bias, which can be difficult or impossible to properly adjust for [54]. Therefore, we recommend validating the NVS using a combination of criterion validation and randomized controlled trials which, when designed appropriately, account for both known and unknown confounders.

The NVS has many strengths. It follows recommendations for developing NPS for global use [8], by solely using essential nutrients of public health priority (excluding nutrients of little public health significance), analyzing locally available, commonly consumed foods and, to the extent possible, using food composition data from LMICs, and offering flexibility for adaptation to different contexts. The NVS also uses nutrient ratios, which recent evidence suggests may identify non-communicable disease risk more accurately than simply using limiting nutrients [9]. Moreover, the NVS follows the best practices for developing NPS for use in environmental impact assessments [16]. Furthermore, the NVS assesses the quantity *and* quality of essential micronutrients and macronutrients, including adjustments for nutrient bioavailability. Importantly, the NVS quantifies nutrient density in terms of mass *and* energy, which ensures foods are not unfairly penalized or benefited for having low or high-Calorie density. Finally, the NVS offers nutritional component scores to provide more granular insights for researchers, food producers, policymakers, and program managers. Notably, the NVS was developed without industry funding or input, to minimize private sector influence and bias. All methods, data, and code are available open access so that other researchers can easily use, validate, and adapt the approach for other settings. These strengths make the NVS suitable for identifying the most nutritious foods to prioritize in policies, investments, and programming globally.

The NVS was not designed as a front-of-package label. Unlike Nutri-Score or HSR, which classify foods into a small number of categories to communicate simple messages to consumers, the NVS produces a continuous score intended to inform policy and programming decisions. Translating the NVS into a consumer-facing label would require simplification, such as grouping scores into categories, and would face practical challenges in many contexts where *1*) nutritious foods like fresh fruits, vegetables, and animal-source foods are commonly sold unpackaged, particularly in informal markets; *2*) regulations and reporting standards for nutritional information are lacking or not widely implemented; and *3*) the food industry (especially small- and medium-sized enterprises, including informal businesses) does not have the capacity and resources to measure and report nutritional information. Nevertheless, provided that the above challenges can be addressed or in contexts where they do not represent major barriers, the component scores, NDS, and overall NVS could inform the design of future front-of-package labeling systems that account for both undernutrition and non-communicable disease risk.

The NVS also has important limitations. It was developed using foods and food composition data from LMICs combined with data from the United States, which limited our ability to include certain dietary attributes that could be helpful in reflecting nutritional value, including added sugar and other additives, polyphenols, beneficial microorganisms, and beneficial bioactive compounds unique to animal-source foods. Furthermore, given that national and regional food composition tables include a limited set of foods and nutrients, which was insufficient to apply the NVS algorithm, we relied on USDA databases for many foods and dietary attributes. This necessary choice may have led to neglecting important differences in varieties, production methods, agroecological conditions, and culinary traditions that exist between the United States and any other country. This underscores a critical challenge for nutrition research in LMICs: the lack of comprehensive, high-quality, locally generated food composition data remains a major barrier to developing context-appropriate tools for food systems policy and programming, and investments in national and regional food composition databases are urgently needed. To implement the NVS in commercial products would likely require a simplified version using available nutrient values commonly measured by food manufacturers. Additionally, we did not include the food category oils and fats in this analysis, as their unique nutritional profiles would have required developing a tailored algorithm with a different set of attributes. Finally, the NVS has not yet been assessed for criterion validity. Future studies could adapt the NVS for broader applications and further assess its validity.

The NVS provides a holistic metric to assess and compare the overall nutritional value of food groups and individual foods, as well as specific nutritional components of interest, like micronutrients and protein. It captures multiple dietary components critical for public health and has many unique features that make it suitable for applications in LMICs. The NVS enables policymakers and program implementers to identify the most nutritious foods for maximum health impact, while providing a functional unit for more meaningful environmental impact and affordability assessments. Although further validation studies will strengthen its applications, the NVS shows promise for advancing healthy and sustainable food systems globally.

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Author contributions

Both authors developed the theory and methods and cowrote the manuscript.

Conflict of interest

The authors report no conflicts of interest.

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Data availability

Data described in the manuscript are available on GitHub: https://github.com/GAINAlliance/NVS

Code availability

All code is available on GitHub: https://github.com/GAINAlliance/NVS

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tjnut.2026.101443.

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