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Modeling Expert Opinions on Food Healthfulness: A Nutrition Metric

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ABSTRACT

Research during the last several decades indicates the failure of existing nutritional labels to substantially improve the healthfulness of consumers' food/beverage choices. The present study aims to fill this void by developing a nutrition metric that is more comprehensible to the average shopper. The healthfulness ratings of 205 sample foods/beverages by leading nutrition experts formed the basis for a linear regression that places weights on 12 nutritional components (ie, total fat, saturated fat, cholesterol, sodium, total carbohydrate, dietary fiber, sugars, protein, vitamin A, vitamin C, calcium, and iron) to predict the average healthfulness rating that experts would give to any food/beverage. Major benefits of the model include its basis in expert judgment, its straightforward application, the flexibility of transforming its output ratings to any linear scale, and its ease of interpretation. This metric serves the purpose of distilling expert knowledge into a form usable by consumers so that they are empowered to make more healthful decisions.

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Despite an increased standard of living in many developed countries, health problems attributable to poor nutrition persist, in part, because of consumers' inability to translate the dietary advice of nutrition experts into behavioral change. Citing the improvement of public health as a primary objective, numerous studies have highlighted the need for a nutritional scoring system that is both comprehensive in its coverage of products and easily understood by consumers (1-5). The present research advances this objective by proposing a nutrition metric that reflects the current views of leading experts and can be used to score any food/beverage for which several component nutrient quantities are known.

Regulatory efforts to improve nutritional labeling have had relatively little effect on individuals who were not already motivated to eat more healthfully (6,7). The complexity of processing nutritional information limits the influence of point-of-purchase labeling (8), especially in fast-food settings (9) or when many options are available (10). It is often difficult for consumers to interpret a food/beverage's contribution to overall diet (11) and to take into consideration the presence of favorable nutrients, given the tendency to focus disproportionately on avoiding negative components (6,12,13). Furthermore, promotional efforts of manufacturers can mislead consumers about what is healthful (1,14,15), and can even exacerbate negative behaviors (16).

Nevertheless, there are indications that nutritional labeling has potential to assist consumers in making more healthful choices. For instance, direct comparability of nutrient information across options induces more advantageous product selections (13,17), and nutrition labeling schemes are more effective when adapted to a target audience or when they employ simple messages promoting taste as well as healthfulness (18). Given specific behavioral recommendations, subsequent decision making is evaluated more favorably according to both consumers' own judgments and expert standards (19). Although marketers will likely continue to tout the healthfulness of their products regardless of true nutritional value, unbiased information can influence consumers' beliefs independently of these claims (20,21), and consumer misperceptions can be mitigated by greater understanding of nutritional components (22).

Several recent studies have developed more detailed guidelines for effective nutritional labeling. Padberg (3) finds a large degree of consensus among experts and calls for an expert rating system that appropriately weights various nutrient factors to summarize any item's nutritional value as part of a daily diet. Toward this end, Nijman and colleagues (2) characterize foods/beverages based on their levels of four unhealthful components (*trans* fat, saturated fat, sugar, and sodium), the generic benchmark levels of which have been established by scientific evidence. However, the final product nutrition score fails to take into consideration the presence of favorable nutrients that also affect healthfulness.

Perhaps the most thorough attempt at outlining desirable features of a nutritional profiling system is provided

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by Scarborough and colleagues (5), who advocate "a systematic, transparent and logical process" to categorize foods by nutritional composition. Scarborough and colleagues (23) evaluated each of eight existing nutrient profile models by the correlation of their ratings with healthfulness categorizations by food and nutrition professionals. The present research builds upon the premise that expert assessments are, in some sense, the most comprehensive embodiment of current scientific knowledge, and goes one step further by actually employing expert ratings to generate a nutrition metric.

METHODS

This study involved surveying US nutrition experts about the healthfulness of sample food/beverage products, estimating the regression equation that best predicts expert ratings from the nutrient information on a Nutrition Facts label, and finally analyzing the applicability of this model to rating the healthfulness of products outside the initial sample. All procedures were reviewed and exempted by the Harvard Business School Institutional Review Board.

Food/Beverage Sample

A large online grocer provided a database containing nutritional information for >15,000 unique food/beverage items. Also listed in the database were the 205 categories used by the grocer to classify items and the unit sales of each item in 2005. In order to create a sample representative of the items that consumers consume most regularly, but also covering a range of food/beverage types, the most frequently purchased item in each category was selected to comprise a sample of 205 foods/beverages for experts to rate. For each of these items, any nutritional information missing from the database was collected by researching similar items online (24,25).

Expert Sample

Participation in the survey was requested of 57 leading nutrition experts belonging to three groups widely recognized for their expertise in nutrition: chairs of the top three schools of public health nutrition departments (ie, Harvard University, John Hopkins University, and the University of North Carolina); directors of the eight US Clinical Nutrition Research and Human Nutrition Centers; and directors of the 46 Coordinated Programs in Dietetics with accredited status from the American Dietetic Association. These experts—all of whom hold doctoral degrees in related fields—were each offered $250 for their consultancy, which required them to complete a 1-hour Web survey. The overall response rate was 23% (13 experts), and no repeated solicitation was undertaken to include others because of strong correlation among these respondents.

Data Collection

The survey asked experts to rate the healthfulness of each of the 205 sample foods/beverages when consumed in the recommended serving size. The item name was displayed along with a picture of the item and a typical Nutrition Facts label. The label listed serving size, servings per container, calories per serving, calories from fat per serving, and the amount per serving of the following 12 components: total fat, saturated fat, cholesterol, sodium, total carbohydrate, dietary fiber, sugars, protein, vitamin A, vitamin C, calcium, and iron.

Experts rated each of the 205 items on an 11-point scale from −5 ("very unhealthy") to 5 ("very healthy"). For each of the 13 experts surveyed, an ordinary least squares regression was run to predict their ratings for the 205 sample foods/beverages using the 12 nutritional components listed on a Nutrition Facts label. For components typically shown in both absolute amount and percentage of daily value on a Nutrition Facts label, only the absolute amounts were included to avoid redundancy. Similarly, "calories per serving" and "calories from fat" were excluded because they can be calculated directly from fat, carbohydrates, protein, and alcohol (which was absent from the foods/beverages in our sample).

Data Analysis

Each expert's linear model was used to predict ratings for the remaining 9,393 database items for which the 12 predictor variables were available. To measure similarity of the 13 experts' models for healthfulness, Cronbach's α was computed across both their original sample ratings and across their model predictions for other items in the database. Cronbach's α is a measure of inter-rater reliability, and values approaching 1 suggest that raters have similar "representations" of the underlying construct (here, healthfulness).

Next, a single linear model was generated to predict the average expert opinion about the healthfulness of a given food/beverage, with the 12 nutritional components on each product's Nutrition Facts label as predictor variables. As for the individual expert models, this model was used to predict average expert ratings for the other 9,393 foods/beverages in the database.

RESULTS AND DISCUSSION

The 13 regression models resulting from individual experts' survey responses indicate the implicit weighting placed on each nutritional component, accounting for a considerable amount of variance in sample ratings (average r^2 of 0.48; average adjusted r^2 of 0.45). Indicating a high level of similarity between experts, Cronbach's α was .95 across their original sample ratings and .98 across their models' predictions for the other 9,393 items in the database. One can infer that the variation left unexplained by each rater's model was caused not by a large rating error, but rather by the exclusion of predictor variables that affect the healthfulness of foods/beverages similarly for all experts. This suggests that the Nutrition Facts label might be missing important components that experts agree affect healthfulness. Despite limiting predictor variables to those available on a Nutrition Facts label, high levels of correlation across experts' judgments justify generation of a single linear model to predict the average expert opinion about the healthfulness of a given food/beverage.

To generate such a model, the 13 expert ratings for each food/beverage were first averaged. Across the 205

Table 1. Model for predicting food/beverage healthiness based on 12 nutritional variables, derived by regressing average expert healthiness ratings (on an 11-point scale from −5="very unhealthy" to 5="very healthy") on these 12 predictor variables for 205 sample foods/beverages

Predictor variables	Coefficient
(Intercept)	0.710*** (0.207)
Total fat (g)	−0.0538 (0.0414)
Saturated fat (g)	−0.423*** (0.0944)
Cholesterol (mg)	−0.00398 (0.00330)
Sodium (mg)	−0.00254*** (0.000445)
Total carbohydrate (g)	−0.0300** (0.0110)
Fiber (g)	0.561*** (0.109)
Sugar (g)	−0.0245 (0.0190)
Protein (g)	0.123*** (0.0222)
Vitamin A (%DV[a])	0.00562* (0.00234)
Vitamin C (%DV)	0.0137*** (0.00399)
Calcium (%DV)	0.0685*** (0.0137)
Iron (%DV)	−0.0186 (0.0186)

[a]Percentage daily value.
*$P<0.05$.
**$P<0.01$.
***$P<0.001$.

Table 2. Average model predictions (more negative numbers indicating greater unhealthiness and more positive numbers indicating greater healthiness) across items within product categories having the 10 highest average predictions and the 10 lowest average predictions

Category name	Average predicted rating within category
Dried beans (generic)	7.87
Natural supplements	7.86
Citrus (fresh)	3.68
Instant breakfast	3.67
Nutritional foods/beverage	3.37
Skim milk	3.35
Diet aids	3.34
Spinach (fresh)	3.26
Organic fruits (fresh)	3.26
Berries (fresh)	3.17
Beef (frozen)	−2.26
Cakes (fresh)	−2.29
Candy chocolate	−2.40
All other frozen breakfast	−2.46
Butter	−2.56
Sausage (fresh)	−2.70
Hot dogs/sausage/brats	−2.84
Pies (fresh)	−2.86
All other fresh bakery	−3.53
Premade lunch packs	−3.65

sample items, the average rating had a mean of 0.30 and a standard deviation of 2.2 on the −5 to 5 scale. Table 1 shows results of a regression model (using robust standard errors to allow for heteroscedasticity) to predict these average expert ratings for a food/beverage based on the 12 nutritional predictors. To summarize, the predicted average rating that experts would give to a food/beverage based on its nutritional components (to three significant digits) is:

$$0.710-0.0538\times total\_fat-0.423\times saturated\_fat-0.00398\times cholesterol-0.00254\times sodium-0.0300\times total\_carbohydrate+0.561\times fiber-0.0245\times sugar+0.123\times protein+0.00562\times vitamin\_A+0.0137\times vitamin\_C+0.0685\times calcium-0.0186\times iron$$

Measurement units are specified in Table 1.

The model's r^2 of 0.626 suggests that it captures almost two thirds of the variance in experts' average ratings of foods/beverages, justifying use of the model to predict the average rating that would be given by experts to the other 9,393 foods/beverages in our database. The 10 highest and 10 lowest average predictions across items within a product category are shown in Table 2. To illustrate the usefulness of comparison within a single category, the 10 highest and 10 lowest predictions for items classified under "All Other Salty Snacks" are shown in Table 3.

CONCLUSIONS

Although the valence of impact that most nutrients have on the healthfulness of a food/beverage might be common knowledge even to lay consumers, the contribution of the model outlined in Table 1 is the assignment of a magnitude weighting to each nutritional component. This allows for isolation of each component's separate impact without compromising the ability to summarize their combined impact in a single metric. Indeed, the model demonstrates that some nutritional components have substantial positive effects on a food's healthfulness, while others have substantial negative effects, implying that previous models focusing solely on one or the other have omitted critical information that experts take into account. While there was a necessary tradeoff between the explanatory power of the present model and its parsimony in predictor variables, it arguably encompasses the most important inputs to the professional judgments of nutrition experts.

This metric for rating healthfulness meets many of the criteria described in the literature, yet widely lacking from prior research. First, the present approach did not require experts to explicitly assign numerical valuations to different nutrients because their ratings for a broad sample of foods/beverages captured implicit judgments about the impact of different nutrients. Second, the decision to generate a model of healthfulness based on average expert ratings was validated by a high level of agreement across individual expert models, and the resulting predictions for average expert rating can be used to compare nutritional values of foods/beverages either across or within product categories. Lastly, the model's predictions fall along a single linear spectrum, and can be easily transformed to any continuous distribution or discrete categorization that is deemed optimal for effectively conveying information to consumers in a particular context.

There are several possible applications for the model. Similar to the work of Scarborough and colleagues (23),

Table 3. Model predictions (more negative numbers indicating greater unhealthiness and more positive numbers indicating greater healthiness) for items having the 10 highest predictions and the 10 lowest predictions in the category "All Other Salty Snacks"

Food in the "all other salty snacks" category	Predicted rating
Guiltless Gourmet Guiltless Carbs Chips Three Pepper[a]	2.97
Guiltless Gourmet Guiltless Carbs Chips Southwestern Ranch[a]	2.84
Guiltless Gourmet Guiltless Carbs Chips Salsa Verde[a]	2.84
Snyder's of Hanover EatSmart Soy Teins Parmesan, Garlic & Olive Oil[b]	2.29
Snyder's of Hanover EatSmart Soy Teins Tomato, Romano & Olive Oil[b]	2.24
Glenny's Soy Crisps Barbeque Low Fat[c]	1.96
Glenny's Soy Crispy Wispys White Cheddar[c]	1.65
Glenny's Soy Crisps Light Low Fat Salted[c]	1.51
Calbee Snack Salad Snapea Crisps Original[d]	1.25
Calbee Snack Salad Snapea Crisps Caesar[d]	1.16
Osem Bissli Snacks Barbecue[e]	−0.99
Osem Bissli Snacks Taco[e]	−1.00
Osem Bissli Snacks Smokey[e]	−1.27
Osem Bissli Snacks Pizza[e]	−1.28
French's Potato Sticks Original[f]	−1.59
Slim Jim Smoked Snacks Spicy, 15 ct[g]	−2.55
Slim Jim Smoked Snacks Mild, 15 ct[g]	−2.55
Jays O-KE-DOKE Corn Puffs[h]	−2.61
Slim Jim Smoked Snacks Spicy, 5 ct[g]	−4.09
Slim Jim Smoked Snacks Mild, 5 ct[g]	−4.09

[a]R.A.B. Food Group, LLC, Secaucus, NJ.
[b]Snyder's of Hanover, Hanover, PA.
[c]Glenny's, Freeport, NY.
[d]Calbee America, Inc, Fairfield, CA.
[e]Osem, Tel-Aviv, Israel.
[f]Reckitt Benckiser, Inc, Parsippany, NJ.
[g]ConAgra Foods, Inc, Omaha, NE.
[h]Jays, Chicago, IL.

its predicted ratings could be correlated with those of lay consumers or those produced by other metrics to determine whether the latter reflect the knowledge of experts in their nutrient weightings. More importantly, the model can be used to generate healthfulness ratings that are displayed alongside food/beverage labels, allowing consumers to make more informed choices about which products to purchase and consume. One limitation, though, is the model's inability to determine combinations of foods/beverages that comprise a well-balanced overall diet because it rates each item in isolation. It can prove most useful to consumers choosing between similar items within the same category. To this end, future studies will test the extent to which outputs of the model help consumers make decisions more closely aligned with recommendations of nutrition experts.

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