The Perception of Food Products in Adolescents, Lay Adults, and Experts: A Psychometric Approach

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Abstract

With nearly 40% of global mortality attributable to dietary factors, citizens are encouraged to eat more healthily. But how do people conceptualize *healthy foods*—and how is this conceptualization embedded in their cognitive representations of food ecology? Adolescents, lay adults, and nutritional experts rated a large, heterogeneous set of food products on a diverse set of characteristics, and we applied the psychometric paradigm pioneered in risk-perception research to identify the dimensions structuring the cognitive representations of those foods. We then used the foods' scores on these dimensions to predict respondents' judgments of the healthiness of those foods. Animal-based nutrients (e.g., cholesterol, fat, protein) and naturalness levels (e.g., processing, artificial additives) were the two central dimensions structuring respondent representations of the foods. Relative to the other two groups, the adolescents' representations were less differentiated. Perceived healthiness was determined by multiple factors, but its strongest predictor was a food's naturalness. These structures emerged for all respondent groups, but there was a high degree of variability among the adolescents.

Keywords: healthiness perception, cognitive representation, psychometric paradigm, individual differences, food decision making

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Dietary factors are linked to a substantial proportion of deaths from noncommunicable diseases (NCDs). These include heart disease, stroke, and type 2 diabetes (Micha et al., 2017), which account for almost 40% of global mortality (Clark, Springmann, Hill, & Tilman, 2019; Institute for Health Metrics and Evaluation, 2020). Partly in response to these insights, one of the key goals of the European Food and Nutrition Action Plan (2015–2020) issued by the World Health Organization (WHO) European Region is to ensure that "all citizens have healthier diets throughout their lives" (WHO, 2015, p .4).

But how do people intuitively conceptualize *healthy* foods? Given that lay people often have only limited knowledge of the healthiness of food (e.g., Hendrie, Coveney, & Cox, 2008), numerous food labels (e.g., the traffic light scheme in the UK, or the keyhole label in the Nordic countries) have been introduced and health claims displayed (e.g., low-calorie, low-fat, no added sugar) with the aim of helping people to make healthier food choices. However, adding a label or a health claim to a product seems to have little (Lähteenmäki, 2013) or no effect (Orquin, 2014) on people's judgments of food healthiness. These findings suggest that "quick fix" solutions like these are not effective (but see Trudel, Murray, Kim, & Chen, 2015). An alternative approach is first to understand better how people cognitively represent the food products they encounter in their environment—that is, food ecology—and how those representations in turn guide their perceptions of a food's healthiness (Ye, Morrin, & Kampfer, 2020).

Previous research on the perception of food healthiness has identified a number of aspects that people take into account when judging the healthiness of food (e.g., fat and salt content, packaging, and health claims). Yet much of this research has been limited to a rather specific selection of aspects. In addition, most studies have involved a narrowly circumscribed set of food products (e.g., fish, apples, vegetable oil). In this article, we complement this approach by (a) considering a large and heterogeneous set of food products, (b) using a bottom-up approach to identify the factors that structure people's cognitive representations of food products, and (c) examining how these cognitive structures are linked to subjective perceptions of food healthiness. A key contribution of our research is that we employ the psychometric paradigm, which was pioneered in research on risk perception (Fischhoff, Slovic, Lichtenstein, Read, & Combs, 1978; Slovic, 1987), to map people's cognitive representations of food products and judgments of food healthiness. To our knowledge, with the exception of Bucher, Collins, Diem, and Siegrist (2016), this approach has not previously been applied to the perception of foods. To contextualize the results, we compare findings for lay people and nutrition experts; to trace possible developmental differences in the perception of food healthiness, we compare adolescents and younger adults.

Previous Research on the Perception of Food Healthiness

Determinants of Subjective Food Healthiness

Research suggests that people rely on a wide variety of cues when judging the healthiness of foods. These cues can be grouped into three main classes: (a) food nutrients, (b) food labels and health-related claims, and (c) peripheral product features (e.g., André, Chandon, & Haws, 2019; Chernev, 2011; Lefebvre & Biswas, 2019; Oakes & Slotterback, 2002; Orquin, 2014; Rizk & Treat, 2014). In the following, we discuss each type of cue in turn.

Food nutrients

Several studies have documented that the nutrients contained in food have an important influence on perceived food healthiness, and that these cues may also interact with other cues.

For instance, of the seven characteristics considered in Oakes and Slotterback's (2002) investigation, fat content and freshness were the most important for respondents judging food healthiness. In another set of studies, the same authors found that when college students judged the healthiness of 33 food products based on their name and serving size, they relied on the fat, mineral, and vitamin content; when provided with the nutritional content, they also took cholesterol levels into account (Oakes & Slotterback, 2001b). Replicating the study with adults aged over 25, Oakes and Slotterback (2001a) showed that this group also took the fiber, sodium, and protein content into account when judging food healthiness. These results echo Paquette's (2005) conclusions from a literature review that a food's naturalness as well as nutrients such as fat, sugar, and salt impact people's perceptions of healthy eating.

Further support for the importance of specific nutrients on perceived food healthiness comes from Nielsen, Sørensen, and Grunert (1997), who found that level of processing, vitamin and mineral content, and fat percentage emerged as important factors contributing to the perceived healthiness of fish. Similarly, Bech-Larsen (2001) focused on apples and found that vitamin content as well as the descriptors "organic" and "wholesome" were the strongest predictors of healthiness judgments in this context. Nielsen, Bech-Larsen, and Grunert (1998) studied perceptions about the healthiness of vegetable oil, and identified unsaturated fat, cholesterol, and naturalness as the key factors for this product type.

In a study by Rizk and Treat (2014), undergraduate women judged the healthiness of 104 foods. They judged foods high in fat, sugar, and protein to be less healthy, and foods high in fiber to be more healthy. Using 54 food items and six food characteristics, Bucher, Müller, and Siegrist (2015) found that fruit/vegetable and fiber content were associated with higher perceived healthiness, whereas sugar and fat content were linked to lower perceived healthiness.

Note that although this research has provided valuable insights into the specific properties of nutritional content that contribute to perceptions of food healthiness, some studies relied on a rather narrow set of products (e.g., Bech-Larsen, 2001; Nielsen, Bech-Larsen, & Grunert, 1998; Nielsen, Sørensen, & Grunert, 1997) and most looked at only a small set of food characteristics. It is currently unclear to what extent the findings hold for food products more generally.

Food labels and health claims

Food labels and nutrition- and health-related claims have also been shown to affect perceptions of food healthiness. For instance, Perkovic and Orquin (2018) found that people judge organic foods to be healthier than conventional foods. In a study on chocolate bars, Schuldt, Muller, and Schwarz (2012) reported that a fair-trade label—which denotes better trading conditions for producers—evoked higher perceived healthiness.

Product features

Finally, certain rather “superficial” cues, such as label color, packaging shape, product texture, name, and price, can influence people’s perceptions of the healthiness of food products. For instance, Schuldt (2013) showed that a green rather than a red label on a candy bar (with the same calorie content) increased perceived healthiness, while Jansson-Boyd and Kobescak (2020) found that the more pronounced the texture of oat biscuits, the healthier they were perceived to be. In a similar vein, Ye et al. (2020) found that products in matte packages were judged as healthier than products in glossy packages. Haws, Reczek, and Sample (2017) explored the relationship between price and perceived healthiness, and found that people believe that healthier foods are more expensive. Finally, Oakes and Slotterback (2001a, 2001b) found that a food’s reputation affects healthiness judgments more than nutritional content.

These findings would not be problematic if superficial cues were used to guide people to healthy food products. However, as the use of product features of this type is currently entirely unregulated, their strategic application can mislead people into buying seemingly healthy products that may, in reality, be harmful to health.

Developmental Differences in the Perception of Foods

Given that perceptions of food healthiness should be linked to knowledge about food and nutrition, an interesting issue—from both a theoretical and an educational point of view—is how the structure and organization of judgments of food healthiness develops ontogenetically. Several studies have shown that while 5- to 10-year-olds usually do not have difficulties classifying whole foods as good or bad, they struggle to classify foods containing several ingredients or foods that can be prepared in different ways (Gosling, Stanistreet, & Swami, 2008; Thompson, Blunden, Brindal, & Hendrie, 2011). In addition, they often cannot provide reasons for their classifications, despite being familiar with nutrients such as vitamins, protein, and fats (Michela & Contento, 1984). This could be because they do not know which nutrients are contained in the relevant food products (Lytle et al., 1997).

Perceptions of food healthiness in 12- to 16-year-olds, by comparison, have been shown to be more differentiated. At this age individuals base their perceptions on specific nutrients such as sugar, fat, and salt, and also seem to consider other information, such as portion size and the presence of additives (Bucher et al., 2016). Thus, adolescents are able to incorporate different characteristics into their assessments, whereas for the majority of younger children, this may be too challenging.

Comparisons of adolescents and younger adults have rarely identified notable differences in the perception of food healthiness, however (for an exception, see Worsley, 1980). Young adults commonly consider nutrients such as fat content when judging food healthiness, but also some other characteristics such as freshness (Oakes & Slotterback, 2001a, 2001b; see also Ronteltap, Sijtsema, Dagevos, & de Winter, 2012). In a study with a large, nationwide U.S. sample that included respondents of various ages, Lusk (2019) found evidence (using exploratory factor analysis) that healthiness perceptions are based on at least three latent dimensions: animal origin, preservation, and freshness/processing. Nutrients such as fat, sodium, carbohydrate, and protein content also affect healthiness perceptions, with all nutrients apart from protein having a negative impact. Thus, both adolescents and adults use specific nutrients (e.g., fat) as well as some other cues (e.g., presence of additives) to gauge food healthiness.

In sum, while food healthiness perceptions become more nuanced from childhood to adolescence, the food healthiness perceptions of adolescents resemble those of adults.

Summary

Previous research has identified a wide range of characteristics that influence perceptions of food healthiness, including food nutrients, food labels, and nutrition- and health-related claims, but also more superficial features, such as packaging. In addition, although perceptions seem to undergo differentiation over ontogenetic development, the most pronounced changes occur between childhood and adolescence, with little evidence for further differentiation in adulthood.

One potential limitation of previous research, however, is that most studies have focused on a fairly limited set of food characteristics and studied homogenous samples. It is therefore unclear to what extent findings hold for the perception of food healthiness more generally. In order to effectively tackle growing obesity rates and the associated NCDs, policymakers need to implement measures informed by a well-founded understanding of how people cognitively represent a broad range of common food products in terms of many characteristics. Against this background, we applied a paradigm previously used in risk research, namely the psychometric paradigm (Fischhoff et al., 1978), to a broad range of common food products, each assessed on a diverse set of food characteristics. Similar to risk perception studies utilizing the psychometric paradigm, our aim was to identify general structures underlying people's perceptions of food products and to test how these general structuring dimensions of food perception are associated with the products' perceived healthiness. We employed this methodological approach to compare the representational structures of adolescents, young adult lay people, and nutrition experts. In what follows, we describe the psychometric paradigm in more detail.

The Psychometric Paradigm

The psychometric paradigm was developed by Fischhoff et al. (1978) to explore the dimensions that structure lay people's subjective perceptions of technological, behavioral, and other hazards (e.g., firearms, tornadoes, nuclear power plants). To that end, multidimensional scaling and other multivariate analysis techniques are employed to generate quantitative representations or "cognitive maps" of people's perceptions of objects in a domain. The most commonly used technique is principal component analysis (PCA), which extracts key components (or factors) from people's ratings of a set of objects (e.g., hazards) that explain common variance across a set of rating scales.

The typical set-up in risk perception research is that respondents are presented with a set of hazards, each of which they rate on a number of characteristics, such as voluntariness, controllability, familiarity, dread, and catastrophic potential. A PCA is then applied to the average (across respondents) ratings of each hazard on the different characteristics, allowing researchers to extract a reduced set of (ideally uncorrelated) dimensions, each summarizing a subset of the characteristics. For instance, several studies have found that the hazards' characteristics can be represented by two key dimensions: a novelty factor (representing characteristics such as observability, familiarity, and delay of consequences) and a dread factor (representing characteristics such as controllability, catastrophic potential, and voluntariness). The hazards can then be classified according to whether they score high or low on each of these factors. For instance, radioactive waste, DNA technology, and nuclear reactor accidents have high scores on both the novelty and dread factors, whereas bicycles, alcohol, and trampolines have low scores on both factors (Slovic, 1987). These factor solutions are assumed to reflect people's cognitive representations of the hazards. The position of the hazards on the factors has also been related to people's responses to the hazards. For instance, people perceive hazards as "riskier" and express a stronger desire for regulation if they score higher on the dread factor (cf. Pachur, Hertwig, & Steinmann, 2012; Slovic, Fischhoff, & Lichtenstein, 1985). The same approach has been used to compare the risk perceptions of laypeople and experts (e.g., Slovic, Fischhoff, & Lichtenstein, 1981).

In the present study, we applied the psychometric paradigm to extract the key dimensions structuring people's representations of food products from their ratings of those products on a large set of characteristics. Each product's score on these dimensions (which represent a subset of the characteristics) yielded a profile of scores for each product that allowed us to derive clusters of food products. The products' scores on the extracted dimensions were subsequently used to predict people's healthiness judgments of these foods.

The Present Study

Our study had four main goals. First, based on respondents' ratings of a large set of food products on a range of consumer-relevant characteristics, we used the psychometric paradigm to identify the key dimensions underlying people's cognitive representations of food products. In contrast to most previous research on food perception, which has focused on a limited set of characteristics, we considered a wide variety of food products and characteristics. Second, we used the products' scores on these dimensions to predict differences in their perceived healthiness, providing insights into the food properties associated with healthiness judgments. Third, to contextualize the results, we collected data from three respondent groups: adolescents, young lay adults, and nutrition experts (for the sake of brevity, we label these groups adolescents, adults, and experts). By comparing the results for adolescents and adults with the "normative" benchmark of the experts, we were able to explore how the groups deviated in their cognitive representations of food products and construction of healthiness judgments. We focused on adolescents and younger adults because they are age ranges during which substantial behavioral, cognitive, and social changes occur. Moreover, these age groups are particularly affected by growing obesity rates (Mokdad et al., 2003; Nittari et al., 2019), and suboptimal eating behaviors in adulthood—which increase the risk of passing on such behaviors to one's children and/or developing NCDs—often take root in adolescence and young adulthood (Parcel, Muraskin, & Endert, 1988; Poobalan, Aucott, Clarke, & Smith, 2014). We deliberately did not include pre-adolescent children in our study because that would require the study material to be adapted to a younger age group, preventing direct comparisons between age groups (see e.g., Nguyen & Murphy, 2003). Fourth and finally, we examined differences in the cognitive representations of food products on the individual level.

Method

Respondents

The *adult group* consisted of *n* = 100 respondents (77 female) aged 18–56 years (median age = 21 years), who were recruited at the University of Basel, Switzerland, via flyers and posters. The *adolescent group* consisted of *n* = 36 students (15 female) aged 13–16 years (median age = 14 years), who were in the second or third grade of a secondary school in the Basel region and recruited in the context of an IT class (participation was voluntary and anonymous; written parental consent was required). The *expert group* (*n* = 68; 66 female) consisted of 51 professional nutritionists and 17 students of nutritional sciences at Bern University of Applied Sciences. They were aged 21–62 years (median age = 30 years) and recruited via email lists. Four experts who provided incomplete data were excluded from the analyses.

Materials

The study consisted of two main parts. In the first part, respondents were presented with a set of 43 common food products (each represented by an image taken from the website of a large Swiss supermarket) and asked “How healthy is this food product?” Responses for each product were given on a seven-point Likert scale (1 = *very unhealthy*; 7 = *very healthy*). No further definition of what was meant by “healthy” was provided. The food products shown were intended to represent a broad range of common products, including food, drinks, fresh and packaged goods, and including both everyday products (milk, bread) and products typically consumed less frequently (cream, pizza). There were two differences in the lists presented to adults and adolescents: guacamole and citrus juice were presented to adults only, whereas canned corn and prepackaged meals were presented to adolescents only. These non-overlapping products were not included in the analyses, which were based on 41 food products. A list of all food products is provided in Appendix A (Table A2).

In the second part of the study, respondents were again presented with each food product and asked to rate them on 17 characteristics that respondents in a prestudy had identified as relevant for judging the healthiness of a food product.[1] The characteristics were fat content, type of fat (e.g., unsaturated), sugar content, vitamin content, salt content, protein content, fiber content, mineral content, calorie content, cholesterol content, carbohydrate content, natural production, recommended proportion of diet (i.e., amount of that food that should be contained in a balanced diet according to the food pyramid), artificial additives, level of processing, origin (local vs. nonlocal), and level of packaging. Respondents rated each of the 43 food products on these characteristics on a seven-point Likert scale, with labels differing slightly depending on the characteristic. For instance, for “fat content,” the scale ranged from 1 = *very little* to 7 = *very much*. For “level of processing,” it ranged from 1 = *low level of processing* to 7 = *high level of processing*. We also collected demographic information such as age, gender, occupation (where appropriate), height, weight, experience and frequency of dieting, and dietary habits. The latter variables were not considered in the analysis. All study materials and the data are available at https://osf.io/n8h9j/?view_only=d291ccdbb0fa4e2b86ea6d993e93930b.

Procedure

The online questionnaire was programmed using Unipark software (Questback GmbH, 2020). The adult and expert groups were invited to the study by an email that contained information about the goal of the study and a link to the questionnaire. Respondents in the adolescent group also completed the questionnaire individually, but while seated together in groups in a computer room at the school. A teacher gave detailed verbal instructions. All

[1] The prestudy included $N = 54$ students from the University of Basel (27 female, average age 40 years, range 17–74 years), who were asked to nominate aspects that they considered relevant for judging the healthiness of a food product in an open-answer format.

respondents received compensation of 20 Swiss Francs for their participation. The order in which the food products and the characteristics were presented was randomized across respondents. All groups took around 60 minutes, on average, to complete the two parts of the study. Due to a programming error, healthiness ratings were recorded for only six of the experts.

Results

We first examined the main dimensions underlying each group's cognitive representation of food ecology. To this end, we conducted—separately for the experts, adults, and adolescents—a PCA on the average (within each group) rating of each of the 41 food products on the 17 characteristics to identify the key underlying dimensions as well as clusters of food products characterized by these dimensions. Next, we analyzed the healthiness judgments of the three groups, to see which products were perceived as more or less healthy and to what extent the adolescents and adults deviated from the expert assessments. We then used the food product scores on the key dimensions identified by the PCA to predict respondents' healthiness judgments, and examined differences in the groups' assessments of the characteristics of the food products. Finally, we examined individual differences in respondents' cognitive representations of food products by performing a three-way principal component analysis (3MPCA).

What Dimensions Underlie Respondents' Perception of the Food Products?

We conducted a separate PCA for each respondent group, using the principal function from the psych package (Revelle, 2019) in R (R Core Team, 2020). Based on eigenvalues and scree plots, we retained four components for the expert and adolescent groups, and three components for the adult group. We used varimax rotation to enhance the interpretability of the solutions. Table 1 shows how the individual characteristics loaded on the resulting principal components for each respondent group.

As Table 1 shows, all principal components (PC) together explained 80% of the total variance both for the experts and the adults, and 83% for the adolescents. Starting with the experts, the characteristics mineral content and natural production had the highest positive loadings on the first PC, while artificial additives and level of processing had the highest negative loadings. We therefore labelled this component “naturalness.” The second PC had the highest loadings for cholesterol and protein content, so we labelled this component “animal protein.” The third PC had the highest loadings for good fat, fat content, and calorie content, so we labelled it “energy.” The fourth PC had the highest loadings for sugar content and carbohydrate content, so we labelled it “refined carbs.”

In the adult group, the characteristics natural production and recommended proportion of diet had the highest positive loadings on the first PC, while artificial additives and level of processing had the highest negative loading; we therefore labelled that component “naturalness.” Cholesterol, fat, salt, and protein content had the highest loadings on the second PC, which we labelled “animal protein.” Carbohydrates and fiber content had the highest loadings on the third PC, which we labelled “non-sweet carbs.”

In the adolescent group, the characteristics level of processing and artificial additives had the highest positive loadings on the first PC, while natural production and recommended proportion of diet had the highest negative loadings; we therefore labelled it “processing.” Protein and cholesterol content and good fat had the highest loadings on the second PC, which we named “animal protein.” Fiber content (positive) and minerals (negative) had the highest loadings for the third PC, which we labelled “high fiber.” Finally, sugar content had the highest loading on the fourth PC, which we labelled “high sugar.”

We used biplots (created with the ggplot function from the ggplot2 package in R; Wickham, 2016) to analyze the PCA solutions graphically. Each biplot in Figure 1 plots the food products (each represented by a dot) based on their scores on the first two PCs extracted (on the x- and y-axis). The spatial vicinity between a food product and a characteristic in the component space indicates how the former scores on the latter: If a food product is located close to a characteristic, it scores highly on that characteristic. The loadings for the first two PCs can be seen on the top and right axes and are represented in the biplots by vectors. The loadings here are interpreted as correlation coefficients between the characteristics and the PCs. The length of each vector is a function of the standard deviation of the characteristics, and the cosines of the angles between the vectors indicate the correlations between the characteristics (angle < 90° = high positive correlation, 90° = no correlation, angle > 90° = high negative correlation). Further, we identified clusters of food products for each respondent group using the NbClust function from the NbClust package (Charrad, Ghazzali, Boiteau, & Niknafs, 2014) in R; the clusters are indicated by different colors in the biplots. To identify the clusters, we used the average (for the respective respondent group) values for each food product on each characteristic as input.[2] Each biplot thus gives an indication of (a) the relationship between the food product scores and characteristics, and (b) how foods cluster together based on the cognitive representation of the respective respondent group.

As shown in Figure 1a, the experts judged, for example, cream, salted nuts, and sausage to be high in fat. Chocolate bars were viewed as highly processed, high in calories, and high in artificial additives, whereas apples, peppers, potatoes, and water were rated to be low in fat and

[2] In the analysis, we set the minimum and maximum number of clusters to two and ten, respectively. We used Euclidean distance (i.e., the square distance between the two vectors) as a distance measure, and employed the complete cluster analysis method (which constrains the distance between two clusters as the maximum distance between two points).

unprocessed. In addition, the experts perceived the latter products to be part of a healthy diet and naturally produced, whereas the opposite applied to ketchup and chocolate bars. Cheese and eggs were rated as high in protein and low in sugar and carbohydrates, whereas cereals, chocolate bars, and chocolate cookies were viewed as containing high levels of sugar and carbohydrates. We identified three clusters of food products for the experts. One cluster comprises foods that undergo little or no processing, are rich in micronutrients, and are considered to be part of a healthy diet ("healthy foods"; e.g., peppers, apples, whole-grain pasta). The other two clusters consist of less healthy foods that are distinguished by whether they are high in sugar ("high-sugar foods"; e.g., chocolate bars, iced tea) or high in calories ("high-calorie foods"; e.g., cream, fish sticks).

Figure 1b shows the biplot for the adults. Similarly to the experts, the adults perceived, for example, chocolate bars and potato chips to be high in calories, highly processed, and high in artificial additives, but apples, peppers, salad, and water to be low in calories, unprocessed, and without artificial additives. In addition, foods such as apples and peppers were viewed as being part of a healthy diet, whereas the opposite held for chips and chocolate bars. Again, cheese and eggs scored high in protein and low in sugar, and iced tea scored low in protein and high in sugar. Potato chips and pizza were viewed as containing high levels of cholesterol, salt, and fat, and bananas, apples, and peppers as containing low levels. The adults' ratings suggested two main clusters of food products: they differentiated food products that are rich in micronutrients, undergo little or no processing, and are considered to be part of a healthy diet ("healthy foods"; e.g., peppers, apples, salmon) from products that are highly processed and high in artificial additives ("processed foods"; e.g., chocolate cookies, chocolate bars). This cluster was somewhat less refined than the "high-sugar"/"high-calorie" distinction found for the experts.

Figure 1c shows the biplot for the adolescents. As can be seen, they perceived potato chips and chocolate bars to be high in calories, fat, and quite processed, but apples, peppers, salad, and water to be low in fat and unprocessed. In addition, the adolescents viewed the latter products as naturally produced and as part of a healthy diet, whereas the opposite held for potato chips and chocolate bars. In this respect, the adolescents' cognitive representations of the foods were in line with those of both the experts and the adults. Further, the adolescents also rated cheese and milk as being high in protein and good fats and low in sugar, and iced tea as being low in protein and high in sugar. Finally, potato chips, French fries, and pizza were viewed as high in salt and low in sugar, whereas bananas, jam, and low-fat yoghurt had the opposite profile. Three main clusters of food products emerged from the adolescents' ratings. As for the experts and adults, one cluster distinguished food products that undergo little or no processing, high in micronutrients, and part of a healthy diet ("healthy foods"; e.g., apples, peppers, salad). The second cluster consists of foods that are part of a common diet ("everyday foods"; e.g., milk, rice, chicken), and in this respect the adolescents' cognitive representations diverge from those of the two other groups. The third cluster is again similar to the clusters identified for experts and adults, comprising foods that are seen as processed, high in calories, and containing artificial additives ("processed foods"; e.g., ketchup, chocolate bars, chocolate cookies).

Summary

The results of the PCA indicate substantial commonality in cognitive representations of the food products across the three respondent groups. The food products are differentiated on two main dimensions: naturalness or processing level and whether they contain animal-based proteins. There are also similarities between the groups in terms of the clusters of food products identified: unprocessed products (e.g., fruits and vegetables) are distinguished from processed products (e.g., sweets and savory ready-to-eat products). Overall, however, the experts' cognitive representation is more differentiated, with food products being spread out relatively evenly across the characteristics. The adults' representation is less differentiated, and the adolescents seem to have a rather polarized “bad vs. good” representation: characteristics with a negative connotation (e.g., level of processing, artificial additives, carbohydrate content) cluster together, as do characteristics with a positive connotation (e.g., natural production, vitamin content).

Healthiness Judgments of the Foods

We next analyzed how the three respondent groups judged the healthiness of the food products. Figure 2 plots the average healthiness ratings for each food product by group; the products are ordered by the healthiness ratings of the experts (in descending order). As can be seen, the adolescents' and adults' ratings are generally aligned with those of the experts. To evaluate their assessments, we computed for each adult and adolescent the rank correlation (across food products) between their healthiness judgments and those of the experts (using the average expert rating for each product). The average correlation coefficient for the adults was high, $r_s = 0.81$ (95% confidence interval (CI) = [0.73, 0.87]); for the adolescents it was somewhat lower, $r_s = 0.63$ (95% CI = [0.38, 0.80]). Note that the 95% CI for the adolescent group was three times wider than that for the adult group, indicating a considerably higher level of heterogeneity in the adolescents.

To shed light on the extent to which the respondents' healthiness judgments were linked to the dimensions of their cognitive representations of the food products identified in the PCA, and how the three groups differed in that regard, we fitted a linear mixed-effects model separately for each group using the lme function from the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018) in R. In contrast to the analyses presented in Figure 2, which were based on aggregate ratings, in this analysis we used each individual's healthiness judgments for each food product, which served as the dependent variable; the principal component scores of each food product served as the independent variable; and we included random intercepts for respondents and food products. To compute a component score for each food product and for each respondent, we used the pseudo-inverse of the rotated loadings for each of the 17 characteristics and multiplied them by the scaled scores that each respondent assigned to each food product based on the 17 characteristics. These scores were subsequently summed for each of the 41 food products and for each respondent.

Experts

As can be seen in Table 2, the experts' healthiness judgments were associated with all four component scores. "Naturalness" was positively associated with healthiness judgments, whereas "animal protein," "energy," and "refined carbs" were negatively associated. In other words, the experts viewed foods as healthier if they scored higher on mineral content and natural production ("naturalness") and lower on cholesterol and protein content ("animal protein"), good fat, fat and calorie content ("energy"), and sugar and carbohydrate content ("refined carbs").

Adults

Two components showed a relationship with adults' healthiness judgments, namely, naturalness and animal protein. Again, the association with naturalness was positive, indicating here that foods scoring higher on natural production and considered part of a healthy diet were perceived as healthier. The association with animal protein was negative, indicating that foods scoring low on cholesterol, fat, protein, and salt content were perceived as healthier.

Adolescents

The healthiness judgments of the adolescents were associated with all four components. Foods scoring lower on level of processing and artificial additives (“processing”), protein and good fat content (“animal protein”), fiber content (“high fiber”), and sugar content (“high sugar”) were perceived as healthier.

Summary

The analysis of the healthiness judgments provided further insights into the three respondent groups’ perceptions of the food products. Both the adults’ and the adolescents’ healthiness judgments were largely aligned with those of the experts, with the adolescents’ judgments showing more deviation and being considerably more heterogeneous than those of the adults. All groups agreed that fruits and vegetables are the healthiest foods and that products such as chips, chocolate bars, and chocolate cookies are the least healthy. However, for some specific products—such as orange juice and salmon—the adults’ and adolescents’ healthiness perceptions systematically diverged from those of the experts.

Linking the healthiness judgments to the results for the food products’ cognitive representations revealed that both the experts’ and the adults’ judgments were most strongly associated with a food’s naturalness, and that the adolescents’ judgments were most strongly associated with the level of processing. In addition, both experts and adolescents rated foods high in sugar to be low in healthiness, whereas both experts and adults perceived foods of animal origin to be low in healthiness.

Level of Agreement in the Food Product Ratings

Although adults’ and adolescents’ representations of food ecology were similar to those of the experts in many respects, there was substantially more variability among the adolescents than among the adults. To quantify the variability across individuals within each group, we computed Krippendorff's alpha coefficient (Krippendorff, 2011) for the individual-level ratings of the food products on the 17 characteristics. Krippendorff's alpha measures the agreement among raters when rating a set of objects, items, or units of analysis with regard to the values of a variable. It ranges from 0 to 1, with 0 denoting a total lack of agreement and 1 denoting perfect agreement. Given that experts are likely to share a knowledge base, they might be expected to display the highest Krippendorff's alpha; to the extent that adolescents have the lowest level of knowledge—and thus the highest level of subjectivity in their ratings—they might be expected to display the lowest Krippendorff's alpha.

To compute a Krippendorff's alpha separately for each group, we used the individual ratings of 17 characteristics for 41 food products. For example, we looked at how each respondent within each group rated apples on sugar content or bananas on fat content. The level of agreement was highest within the expert group ($\alpha = .691$), lower within the adult group ($\alpha = .522$), and lowest within the adolescent group ($\alpha = .175$). We also analyzed the level of agreement across the individual food products and characteristics; these results are reported in Appendix A.

The analyses thus confirmed that there were considerable differences between the three groups in terms of the unanimity of ratings of the food products on the characteristics, with the highest agreement among the experts, followed by the adults, and then the adolescents. These insights are relevant for two main reasons. First, they are consistent with the idea that the experts share a nutritional knowledge base, leading them to rate the food products in highly similar ways, whereas the adolescents as yet lack such a consensual view. Second, they emphasize that it may be important to take non-aggregated data into account when extracting the key dimensions underlying people's perception of food ecology—an issue to which we turn next.

Three-Way Principal Component Analysis

Far from being unanimous in their ratings of the food products, the respondents—and particularly the adolescents—showed notable variability. One potential limitation of the PCA presented earlier is that it ignores these individual differences. We therefore additionally ran a three-way principal component analysis (3MPCA; for details, see Kiers & Van Mechelen, 2001), which enabled us to analyze the non-aggregated data from all respondents, arranged in a three-dimensional matrix representing the individuals, the food products, and the characteristics, respectively. This analysis yielded a component structure for each of the three "modes," making it possible to assess which structures differentiate the elements in each mode.

We conducted the 3MPCA using the ThreeWay package (Giordani, Kiers, & Del Ferraro, 2014) in R and applying the seven main steps proposed by Kiers and Van Mechelen (2001). A detailed description of each step is provided in Appendix B. Here, we focus on the final step (interpreting and reporting the solution). The results suggested that the best-fitting model was the one with three components for the "persons" mode, four components for the "characteristics" mode, and three components for the "food products" mode. In the following, we interpret each of the components separately for each mode.

"Characteristics" mode

The first component of the "characteristics" mode, which is closest to that analyzed by the PCA, had the highest component values for cholesterol, salt, sugar and fiber content.[3] We labelled this component "silent killers" because excessive consumption of foods high in those contents contributes to NCDs (e.g., diabetes, cardiovascular disease, etc.). The second

[3] Component values can only be compared within components, that is, they are normalized to unit sums of squares column-wise, this is the main difference to the component loadings from the two-way PCA. For details, see Kiers and van Mechelen (2001).

component had the highest component values for calorie content and level of processing. We labelled this component "modern vices," because it describes unhealthy characteristics that are becoming increasingly popular among today's consumers. The third component had the highest component values for mineral, vitamin, and protein content and for origin. We labelled this component "healthy diet." The fourth component had the highest component values for carbohydrate content and was labelled "carbs." For details on this mode and its components, see Table B2.

Comparing these results with those obtained with the PCA shows a number of similarities: the "silent killers" component is most similar to the "animal protein" component in the expert and adult groups. The "modern vices" component bears some similarity to the "processing" component obtained for the adolescent group. The "healthy diet" component is most similar to the "naturalness" component in the expert and adult groups, and the "carbs" component is most similar to the "refined carbs" and "non-sweet carbs" components in the expert and adult groups, respectively.

"Food products" mode

The first component of the "food products" mode had the highest component values for cheese, eggs, and salmon and was thus labelled "protein-rich foods." The second component had the highest component values for potatoes and apples and was named "fruits and vegetables." The third component had the highest component values for the processed foods such as pizza, chocolate cookies, and French fries. However, none of the component values exceeded the cut-off value of .3 (see Table B3). We labelled this component "processed foods."

In some sense, the "food products" mode can be related to the clusters of food products identified in the biplots. Comparing the results of the two types of analyses shows that the "protein-rich foods" component corresponds most closely to the "everyday foods" cluster in the biplot for the adolescents. There is also an obvious link between the "fruits and vegetables" component and the "healthy foods" cluster that emerged for all groups. Additionally, the "processed foods" component corresponds to the eponymous cluster in the biplots for the adults and adolescents as well as to the "high-sugar foods" and "high-calorie foods" clusters in the biplot for the experts.

"Persons" mode

The 3MPCA identified three components along which respondents differed in their assessments. We drew on the so-called core array (Kiers & Van Mechelen, 2001), which is reported in Table 3, to interpret the components. The core array expresses the importance of each combination of components for the different modes. For instance, it indicates to what extent respondents who score high on a person component give ratings that have high weights on the characteristics component, for foods that have high weights on a specific food products component. The highest core entries indicate where the largest individual differences occurred.

The first component of the "persons" mode distinguishes individuals in terms of whether they perceive protein-rich foods as being part of a healthy diet and with regard to their perceptions of carbohydrate content. It also distinguishes individuals in terms of whether they perceive fruits and vegetables as modern vices, part of a healthy diet, and with regard to their perceptions of carbohydrate content. Finally, this component distinguishes individuals in terms of the extent to which they see processed foods as modern vices and with regard to their perceptions of carbohydrate content. Taken together, a person scoring high on this component perceives protein-rich foods and fruits and vegetables as belonging to a healthy diet, perceives protein-rich foods as low in carbohydrates but both fruits and vegetables and processed foods as high in carbohydrates, and views processed foods but not fruits and vegetables as a modern vice. The highest score within this component was for perceiving processed foods as modern vices; we therefore labelled it "processed foods as modern vices." The second component is simpler in structure; a person with a high score on this component does not regard processed foods as silent killers. We labelled this component "processed foods not all that bad." Finally, a person with a high score on the third component perceives processed foods to be part of a healthy diet. We labelled this component "processed foods as a healthy diet."

To what extent do the structures identified for the "persons" mode align with our distinction between the three respondent groups? To address this question, we tested how the respondent groups differed with regard to their values on the person components identified in the 3MPCA. Welch's ANOVA showed significant differences between the groups on all three person components ("processed foods as modern vices": $F(2, 96) = 228.96$, $p < .001$, $\omega_p^2 = .67$, 95% CI [.60, .73]; "processed foods not all that bad": $F(2, 83) = 47.92$, $p < .001$, $\omega_p^2 = .23$, 95% CI [.13, .33]; "processed foods as a healthy diet": $F(2, 96) = 44.38$, $p < .001$, $\omega_p^2 = .30$, 95% CI [.20, .39]). Post hoc comparisons for the component "processed foods as modern vices" revealed significant differences between all groups (experts vs. adolescents: $F(1, 80) = 460.36$, $p < .001$, $\omega_p^2 = .81$, 95% CI [.75, .85]; experts vs. adults: $F(1, 135) = 132.83$, $p < .001$, $\omega_p^2 = .44$, 95% CI [.34, .54]; adolescents vs. adults: $F(1, 70) = 165.15$, $p < .001$, $\omega_p^2 = .52$, 95% CI [.40, .61]), with the experts scoring higher ($M = 0.069$, $SD = 0.041$) than both the adults ($M = -0.007$, $SD = 0.041$) and the adolescents ($M = -0.102$, $SD = 0.036$). In other words, the experts perceived processed foods as modern vices to a greater extent than the adults or the adolescents.

Post hoc comparisons for the component "processed foods not all that bad" showed significant differences between the experts and the adolescents, $F(1, 44) = 7.98$, $p = .007$, $\omega_p^2 =$

.10, 95% CI [.01, .22] and between the experts and the adults, $F(1, 159) = 96.17$, $p < .001$, $\omega_p^2 = .34$, 95% CI [.22, .44], as well as a marginal difference between the adolescents and the adults, $F(1, 46) = 3.93$, $p = .053$, $\omega_p^2 = .03$, 95% CI [−.01, .12], with the experts again scoring higher (*M* = 0.047, *SD* = 0.043) than both the adults (*M* = −0.031, *SD* = 0.059) and the adolescents (*M* = 0.002, *SD* = 0.092). That is, viewing processed foods as not all that bad was more pronounced among the experts than among the adults and the adolescents.

Post hoc comparisons for the final component, “processed foods as a healthy diet,” again revealed significant differences between all groups (experts vs. adolescents: $F(1, 73) = 6.40$, $p = .014$, $\omega_p^2 = .05$, 95% CI [−.01, .16]; experts vs. adults: $F(1, 147) = 49.61$, $p < .001$, $\omega_p^2 = .22$, 95% CI [.12, .32]; adolescents vs. adults: $F(1, 71) = 72.69$, $p < .001$, $\omega_p^2 = .32$, 95% CI [.19, .43]). However, here the adolescents scored significantly higher (*M* = 0.057, *SD* = 0.055) than both the experts (*M* = 0.028, *SD* = 0.055) and the adults (*M* = −0.038, *SD* = 0.063). That is, the adolescents viewed processed foods as part of a healthy diet to a greater extent than the experts or the adults.

Summary

The 3MPCA, which acknowledges individual differences in respondents’ cognitive representations of processed foods, identified differences between groups that were not revealed by the PCA. Specifically, the experts seem to consider processed foods as both “modern vices” but also as “not all that bad” to a larger extent than the adults or the adolescents; and the adolescents considered processed foods as “part of a healthy diet” to a greater extent than the experts or the adults.

Discussion

For almost half a century, scholars in various disciplines have tried to understand people's perceptions of the "healthiness" of different food products. Using the psychometric paradigm developed to study risk perceptions, we identified key dimensions underlying people's perceptions of food ecology and the (dis)similarities in their healthiness judgments. We used the same study material across three respondent groups, enabling us to compare adolescents and adults with a benchmark group of nutrition experts. Overall, the adults and adolescents relied on similar dimensions as the experts to differentiate food products, especially with respect to sugar and carbohydrate content, but also the level of processing involved and perceived naturalness. However, the adolescents' cognitive representations were less similar to the experts' than were the adults', suggesting that knowledge and experience influence people's perceptions of food ecology. Specifically, adolescents' representations were not as differentiated as those of the experts and adults, but showed a greater tendency to cluster food products and characteristics (e.g., cholesterol, calorie, and fat content) together. Overall, the adolescents' cognitive representations seemed to be more polarized, with their perceptions of food ecology being characterized by a good/bad dichotomy, indicating that they are unable to make the same nuanced, fine-grained distinctions between food products as the experts and, to some extent, adults.

Regarding healthiness judgments, all groups were generally in agreement about what is and what is not healthy. However, the adolescents were again less similar to the experts than were the adults, in that their judgments showed a lower correlation with those of the expert ratings and a higher level of heterogeneity. In a multilevel regression analysis, the perceived naturalness of a food product emerged as the strongest predictor of healthiness judgments in all three respondent groups. The 3MPCA revealed that whereas experts and adults seem to regard processed foods as modern vices, (some of) the adolescents saw them as part of a healthy diet.

Our study makes several important contributions. A first methodological contribution is our application of the psychometric paradigm to identify the key dimensions that structure people's cognitive representations of food ecology. Our results thus offer novel insights with respect to how food ecology is cognitively manifested in individuals (but see Bucher et al., 2016). A second methodological contribution is that we used a diverse set of food products and relevant characteristics, thus offering a more generalizable understanding of the link between cognitive representations of food ecology and healthiness judgments than has been the case in much previous research. Instead of focusing on how a narrow set of characteristics (e.g., sugar or fat content) affects people's judgments of food healthiness, we did not use predetermined categories, but relied on a bottom-up approach, in which our PCA results served as a guide for drawing inferences about people's healthiness judgments. Thus, our approach offers a complementary view on the key dimensions underlying people's perceptions of food ecology.

A third methodological contribution is our comparison of adolescents, lay adults, and experts, which allowed the two former groups to be evaluated against a "normative" benchmark. This approach provides more nuanced insights into developmental differences in perceptions of food products and the dimensions underlying healthiness judgments as a function of experience, expertise, and age. To our knowledge, our investigation is the first to compare lay people of different ages with experts in terms of their cognitive representations of food ecology. Moreover, several previous studies addressing health-related phenomena across age groups have adjusted the study material depending on respondents' age, making direct comparisons across age groups difficult. We used the same material for all age groups, enabling us to more confidently capture differences as a function of experience, expertise, and age.

Our work has important implications for public policy, marketing, and nutrition education. Communication campaigns intended to promote public health may benefit from tailoring their messaging to the target group in question. Similarly, marketers, advertisers, and brand owners can draw on the present results to strategically signal healthiness on product packaging, in in-store displays, and in online and offline advertising, to steer people's choices towards healthier food alternatives. Specifically, our results indicate that the naturalness/processing level is an important dimension of how people cognitively represent food ecology and, in turn, perceive the healthiness of food products. To some extent, the same applies to sugar content. Communication campaigns used for public health purposes should therefore clearly indicate the processing level and sugar content of food products, and preferably combine such information with descriptive details directed toward the target group. For instance, given that adolescents were more inclined to perceive processed foods as healthy, it may be more important to clearly communicate the potential long-term harms of consuming such foods to this age group, while simultaneously providing information about the health status of these foods (e.g., through easily recognizable labeling schemes, such as traffic lights or warning signs; see Ares et al., 2020; Rojas-Rivas et al., 2020). In contrast, considering that the adults and experts tended to perceive processed foods as modern vices, these groups (and arguably other older, experienced consumers) may be more easily persuaded by vividly communicating that indulging in momentary pleasures may eventually lead to chronic health problems. Indeed, such a balanced imaging technique (thinking about both positive and negative events) has recently been shown to make people better able to resist temptation in the presence of appetitive, visceral cues (for another food-related imagery effect, see Christian et al., 2016; Cowan, 2019).

Our findings also inform nutrition education, especially efforts aimed at increasing younger individuals' nutritional knowledge. In our study, the adolescents showed a much greater heterogeneity than the adults and experts regarding certain food products and characteristics. For example—as the additional results in Appendix A show—there were large individual differences in the adolescents' ratings of cholesterol content, good fat, and carbohydrate content, as well as low levels of agreement for several food products high in cholesterol (e.g., fast food such as sausage, French fries, and pizza), good fat (e.g., salmon), and carbohydrate content (e.g., ketchup, iced tea, and pasta). Thus, while all age groups showed a high level of agreement in their ratings of apples, consistent with the "apple a day" maxim, nutrition educators would be well advised to strategically target those characteristics and food products where people in general, and young people in particular, provide the most heterogeneous responses.

Effective strategies are clearly needed at a time when obesity rates among adolescents and younger adults have doubled in many countries over the last four decades (Mokdad et al., 2003; Nittari et al., 2019). Over 60% of children who are overweight before puberty remain so in adulthood (Nittari et al., 2019). Suboptimal eating behaviors developed in childhood serve as a basis for maladaptive food choices in adulthood, which in turn increase the risk of both passing on such behaviors to one's children and developing NCDs (Parcel et al., 1988; Poobalan et al., 2014; WHO, 2017). Good and health literacy as well as nutritional skills are considered as prerequisites for a healthy diet throughout life (WHO, 2015), and our findings should make a useful contribution to promoting physical health and wellbeing among people.

We should acknowledge some potential limitations of our findings. The sizes of our samples differed across respondent groups; as such, the differences in factor structures obtained may, to some extent, may reflect differences in the reliability of these factor structures across the groups. Additionally, given the rather low number of experts for whom healthiness ratings were collected, replication of this analysis with a larger set of expert data is warranted. Second, the proportion of female respondents differed across groups, which may have influenced the results. However, it should be noted that while some gender differences have been found in previous studies, they are typically relatively small (Oakes & Slotterback, 2001a, 2001b), and are therefore unlikely to have a substantial impact on our results. Still, future research would benefit from using a larger, more heterogeneous sample of respondents, from different (but similarly sized) age groups and with different levels of expertise in the food domain.

To conclude, the perceived healthiness of food products seems to be firmly rooted in people's general representations of food ecology. It is driven, in part, by more peripheral aspects, such as the level of processing, but also by the proportion of animal-based nutrients contained in the food, such as cholesterol, fat, and protein content. These cognitive structures are already visible among adolescents, but there are considerable individual differences in this age group. Identifying and targeting specific individuals at the fringes of the distribution at an early age might therefore be an effective strategy for shaping and improving nutritional cognition.

References

André, Q., Chandon, P., & Haws, K. (2019). Healthy through presence or absence, nature or science?: A framework for understanding front-of-package food claims. *Journal of Public Policy and Marketing*, *38*(2), 172–191. https://doi.org/10.1177/0743915618824332

Ares, G., Antúnez, L., Otterbring, T., Curutchet, M. R., Galicia, L., Moratorio, X., & Bove, I. (2020). Sick, salient and full of salt, sugar and fat: Understanding the impact of nutritional warnings on consumers' associations through the salience bias. *Food Quality and Preference*. https://doi.org/10.1016/j.foodqual.2020.103991

Bech-Larsen, T. (2001). Model-based development and testing of advertising messages: A comparative study of two campaign proposals based on the meccas model and a conventional approach. *International Journal of Advertising*, *20*(4), 499–519. https://doi.org/10.1080/02650487.2001.11104908

Bucher, T., Collins, C., Diem, S., & Siegrist, M. (2016). Adolescents' perception of the healthiness of snacks. *Food Quality and Preference*, *50*, 94–101. https://doi.org/10.1016/j.foodqual.2016.02.001

Bucher, T., Müller, B., & Siegrist, M. (2015). What is healthy food? Objective nutrient profile scores and subjective lay evaluations in comparison. *Appetite*, *95*, 408–414. https://doi.org/10.1016/j.appet.2015.08.005

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: an R package for determining the relevant number of clusters in a data set. *Journal of Statistical Software*, *61*(6), 1–36. Retrieved from http://www.jstatsoft.org/v61/i06/

Chernev, A. (2011). The dieter's paradox. *Journal of Consumer Psychology*, *21*(2), 178–183. https://doi.org/10.1016/j.jcps.2010.08.002

Christian, B. M., Miles, L. K., Kenyeri, S. T., Mattschey, J., & Neil Macrae, C. (2016). Taming temptation: Visual perspective impacts consumption and willingness to pay for unhealthy foods.

Journal of Experimental Psychology: Applied, *22*(1), 85–94. https://doi.org/10.1037/xap0000067

Clark, M. A., Springmann, M., Hill, J., & Tilman, D. (2019). Multiple health and environmental impacts of foods. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(46), 23357–23362. https://doi.org/10.1073/pnas.1906908116

Cowan, K. (2019). Anything you can imagine is possible: How imagining can overcome visceral drive states elicited in promotional advertising. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2019.04.008

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sciences*, *9*(2), 127–152. https://doi.org/10.1007/BF00143739

Giordani, P., Kiers, H. A. L., & Del Ferraro, M. A. (2014). Three-way component analysis using the R package ThreeWay. *Journal of Statistical Software*, *57*(7), 1–23. https://doi.org/10.18637/jss.v057.i07

Gosling, R., Stanistreet, D., & Swami, V. (2008). "If Michael Owen drinks it, why can't I?" - 9 And 10 year olds' perceptions of physical activity and healthy eating. *Health Education Journal*, *67*(3), 167–181. https://doi.org/10.1177/0017896908094635

Haws, K. L., Reczek, R. W., & Sample, K. L. (2017). Healthy diets make empty wallets: The healthy = expensive intuition. *Journal of Consumer Research*, *43*(6), 992–1007. https://doi.org/10.1093/jcr/ucw078

IHME. (2020). GBD compare. Retrieved January 22, 2020, from https://vizhub.healthdata.org/gbd-compare/

Jansson-Boyd, C. V., & Kobescak, M. (2020). To see is to hold: Using food surface textures to communicate product healthiness. *Food Quality and Preference*, *81*. https://doi.org/10.1016/j.foodqual.2019.103866

Kiers, H. A. L., & Van Mechelen, I. (2001). Three-way component analysis: Principles and illustrative application. *Psychological Methods*, *6*(1), 84–110. https://doi.org/10.1037//1082-989X.6.1.84

Krippendorff, K. (2011). Computing Krippendor ’s alpha-reliability. Retrieved January 11, 2020, from http://repository.upenn.edu/asc_papers/43

Lefebvre, S., & Biswas, D. (2019). The influence of ambient scent temperature on food consumption behavior. *Journal of Experimental Psychology: Applied*, *25*(4), 753–764. https://doi.org/10.1037/xap0000226

Lusk, J. L. (2019). Consumer beliefs about healthy foods and diets. *PLoS One*, *14*(10), 1–15. https://doi.org/10.1371/journal.pone.0223098

Lytle, L., Eldridge, A. L., Kotz, K., Piper, J., Williams, S., & Kalina, B. (1997). Children's interpretation of nutrition messages. *Journal of Nutrition Education*, *29*(3), 128–136.

Lähteenmäki, L. (2013). Claiming health in food products. *Food Quality and Preference*, *27*(2), 196–201. https://doi.org/10.1016/j.foodqual.2012.03.006

Micha, R., Peñalvo, J. L., Cudhea, F., Imamura, F., Rehm, C. D., & Mozaffarian, D. (2017). Association between dietary factors and mortality from heart disease, stroke, and type 2 diabetes in the United States. *JAMA - Journal of the American Medical Association*, *317*(9), 912–924. https://doi.org/10.1001/jama.2017.0947

Michela, J. L., & Contento, I. R. (1984). Spontaneous classification of foods by elementary school-aged children. *Health Education & Behavior*, *11*(1), 57–76. https://doi.org/10.1177/109019818401100103

Mokdad, A. H., Ford, E. S., Bowman, B. A., Dietz, W. H., Vinicor, F., Bales, V. S., & Marks, J. S. (2003). Prevalence of obesity, diabetes, and obesity-related health risk factors, 2001. *Journal of the American Medical Association*, *289*(1), 76–79. https://doi.org/10.1001/jama.289.1.76

Nguyen, S. P., & Murphy, G. L. (2003). An apple is more than just a fruit: Cross-classification in children's concepts. *Child Development*, *74*(6), 1783–1806. https://doi.org/10.1046/j.1467-8624.2003.00638.x

Nielsen, N. A., Bech-Larsen, T., & Grunert, K. G. (1998). Consumer purchase motives and product perceptions: A laddering study on vegetable oil in three countries. *Food Quality and Preference, 9*(6), 455–466. https://doi.org/10.1016/s0950-3293(98)00022-6

Nielsen, N. A., Sørensen, N. K., & Grunert, K. G. (1997). Consumer motives for buying fresh or frozen plaice: A means-end chain approach. In J. B. Luten, T. Børresen, & J. Oehlenschlager (Eds.), *Seafood from producer to consumer – An integrated approach to quality* (pp. 31–43). Amsterdam: Elsevier.

Nittari, G., Scuri, S., Petrelli, F., Pirillo, I., Di Luca, N. M., & Grappasonni, I. (2019). Fighting obesity in children from European world health organization member states. Epidemiological data, medical-social aspects, and prevention programs. *Clinica Terapeutica*, *170*(3), 223–230. https://doi.org/10.7417/CT.2019.2137

Oakes, M. E., & Slotterback, C. S. (2001a). Judgements of food healthfulness: Food name stereotypes in adults over age 25. *Appetite*, *37*(1), 1–8. https://doi.org/10.1006/appe.2001.0405

Oakes, M. E., & Slotterback, C. S. (2001b). What's in a name? A comparison of men's and women's judgements about food names and their nutrient contents. *Appetite*, *36*(1), 29–40. https://doi.org/10.1006/appe.2000.0365

Oakes, M. E., & Slotterback, C. S. (2002). The good, the bad, and the ugly: Characteristics used by young, middle-aged, and older men and women, dieters and non-dieters to judge healthfulness of foods. *Appetite*, *38*(2), 91–97. https://doi.org/10.1006/appe.2001.0444

Orquin, J. L. (2014). A Brunswik lens model of consumer health judgments of packaged foods. *Journal of Consumer Behavior*, *13*, 270–281. https://doi.org/10.1002/cb.1465

Pachur, T., Hertwig, R., & Steinmann, F. (2012). How do people judge risks: Availability heuristic, affect heuristic, or both? *Journal of Experimental Psychology: Applied*, *18*(3), 314–330. https://doi.org/10.1037/a0028279

Paquette, M.-C. (2005). Perceptions of healthy eating: state of knowledge and research gaps. *Canadian Journal of Public Health*, *96*(3), S15–S19.

Parcel, G. S., Muraskin, L. D., & Endert, C. M. (1988). Community education: Study group report. *Journal of Adolescent Health Care*, *9*(6), S41–S45. https://doi.org/10.1016/0197-0070(88)90008-3

Perkovic, S., & Orquin, J. L. (2018). Implicit statistical learning in real-world environments leads to ecologically rational decision making. *Psychological Science*, *29*(1), 34–44. https://doi.org/10.1177/0956797617733831

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team. (2018). nlme: Linear and nonlinear mixed effects models. Retrieved from https://cran.r-project.org/package=nlme

Poobalan, A. S., Aucott, L. S., Clarke, A., & Smith, W. C. S. (2014). Diet behaviour among young people in transition to adulthood (18–25 year olds): a mixed method study. *Health Psychology and Behavioral Medicine*, *2*(1), 909–928. https://doi.org/10.1080/21642850.2014.931232

Questback GmbH. (2020). EFS Survey, Version EFS Winter 2018. Cologne: Questback GmbH.

R Core Team. (2020). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing.

Revelle, W. (2019). psych: Procedures for personality and psychological research. Northwestern University, Evanston, Illinois, USA.

Rizk, M. T., & Treat, T. A. (2014). An indirect approach to the measurement of nutrient-specific perceptions of food healthiness. *Annals of Behavioral Medicine*, *48*(1), 17–25. https://doi.org/10.1007/s12160-013-9569-4

Rojas-Rivas, E., Antúnez, L., Cuffia, F., Otterbring, T., Aschemann-Witzel, J., Giménez, A., & Ares,

G. (2020). Time orientation and risk perception moderate the influence of sodium warnings on food choice: Implications for the design of communication campaigns. *Appetite*, *147*. https://doi.org/10.1016/j.appet.2019.104562

Schuldt, J. P. (2013). Does green mean healthy? Nutrition label color affects perceptions of healthfulness. *Health Communication*, *28*(8), 814–821. https://doi.org/10.1080/10410236.2012.725270

Schuldt, J. P., Muller, D., & Schwarz, N. (2012). The “fair trade” effect: Health halos from social ethics claims. *Social Psychological and Personality Science*, *3*(5), 581–589. https://doi.org/10.1177/1948550611431643

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1981). Rating the risks. In *Risk/benefit analysis in water resources planning and management* (pp. 193–217). Springer, Boston, MA.

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1985). Characterizing perceived risk. In R. W. Kates, C. Hohenemser, & J. X. Kasperson (Eds.), *Perilous progress: Managing the hazards of technology* (pp. 91–125). CO: Westview: Boulder.

Thompson, K., Blunden, S., Brindal, E., & Hendrie, G. (2011). When food is neither good nor bad: Children’s evaluations of transformed and combined food products. *Journal of Child Health Care*, *15*(4), 261–271. https://doi.org/10.1177/1367493511414449

Trudel, R., Murray, K. B., Kim, S., & Chen, S. (2015). The impact of traffic light color-coding on food health perceptions and choice. *Journal of Experimental Psychology: Applied*, *21*(3), 255–275. https://doi.org/10.1037/xap0000049

WHO. (2015). European food and nutrition action plan 2015 – 2020. Retrieved January 30, 2020, from http://www.euro.who.int/__data/assets/pdf_file/0008/253727/64wd14e_FoodNutAP_140426.pdf

WHO. (2017). New global estimates of child and adolescent obesity released on World Obesity Day. Retrieved February 5, 2020, from https://www.who.int/end-childhood-obesity/news/new-estimate-child-adolescent-obesity/en/

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag.

Worsley, A. (1980). Thought for food: Investigations of cognitive aspects of food. *Ecology of Food and Nutrition*, *9*, 65–80.

Ye, N., Morrin, M., & Kampfer, K. (2020). From glossy to greasy: The impact of learned associations on perceptions of food healthfulness. *Journal of Consumer Psychology*, *30*(1), 96–124. https://doi.org/10.1002/jcpy.1126

Table 1

Loadings of the 17 Characteristics on the PCA Solutions by Respondent Group

Characteristic	Experts				Adults			Adolescents			
	Naturalness	Animal protein	Energy	Refined carbs	Naturalness	Animal protein	Non-sweet carbs	Processing	Animal protein	High fiber	High sugar
Artificial additives (1 = very few)	**−0.91**	0	0.14	0.26	**−0.97**	0.14	−0.06	**0.82**	0.15	0.23	0.32
Level of processing (1 = little processing)	**−0.88**	−0.10	0.27	0.25	**−0.94**	0.21	0.04	**0.93**	0.06	0.22	0.06
Level of packaging (1 = little packaging)	**−0.80**	0.09	0.07	−0.08	**−0.64**	0.31	−0.21	**0.71**	0.03	−0.36	−0.12
Calorie content (1 = very few)	−0.42	0.28	**0.72**	0.42	**−0.68**	0.60	0.24	**0.78**	0.52	0.09	0.19
Salt content (1 = very little)	−0.37	0.10	**0.63**	−0.24	−0.20	**0.70**	0.39	0.53	0.49	0.20	**−0.58**
Fat content (1 = very little)	−0.31	0.42	**0.78**	−0.03	−0.44	**0.82**	0.08	**0.76**	0.56	0.06	0.12
Sugar content (1 = very little)	−0.29	−0.07	−0.20	**0.84**	**−0.72**	−0.46	−0.01	0.54	−0.01	0.06	**0.81**
Cholesterol content (1 = very little)	−0.28	**0.83**	0.27	−0.16	−0.34	**0.89**	−0.08	0.59	**0.74**	0.01	0.02
Carbohydrate content (1 = very little)	−0.05	−0.34	−0.05	**0.77**	−0.16	0.18	**0.88**	**0.65**	0.58	0.19	0.04
Protein content (1 = very little)	0.13	**0.68**	0.30	−0.22	0.37	**0.70**	−0.18	0.03	**0.81**	−0.13	−0.10
Good fat (1 = very little)	0.17	−0.06	**0.85**	−0.20	**0.87**	−0.36	0.07	−0.13	**0.74**	0.22	−0.04
Origin (1 = from a distant country)	0.28	**0.56**	−0.43	−0.07	**0.58**	0.09	−0.34	**−0.64**	0.30	−0.41	0.17
Fiber content (1 = very little)	**0.63**	−0.60	0.07	0.02	0.53	−0.25	**0.76**	−0.13	0.52	**0.66**	0.06
Recommended proportion of a healthy diet (1 = small proportion)	**0.75**	−0.14	−0.43	−0.37	**0.86**	−0.43	0.02	**−0.92**	−0.10	−0.18	−0.23
Vitamin content (1 = very few)	**0.87**	−0.18	−0.01	0.06	0.53	**−0.68**	0.08	**−0.91**	−0.12	0.15	0.15
Natural production (1 = not naturally produced)	**0.88**	0.16	−0.17	−0.24	**0.93**	−0.20	−0.05	**−0.93**	0.14	−0.17	−0.18
Mineral content (1 = very little)	**0.91**	−0.02	−0.09	−0.13	**0.79**	−0.38	−0.08	−0.26	0.01	**−0.77**	0.02
Eigenvalues	6.26	2.32	2.96	2.00	7.60	4.25	1.78	7.65	3.33	1.67	1.32
Proportion of explained variance	0.37	0.14	0.17	0.12	0.45	0.25	0.10	0.45	0.20	0.10	0.08
Total variance explained (%)	80				80			83			

Note. Loadings in bold represent the highest absolute loading for a specific characteristic. PC = principal component

Table 2

Results from Mixed-Effects Regression for Experts, Adults, and Adolescents

Respondent Group	Term	Estimate	SE	95% CI
Experts				
	Intercept	5.67	0.13	[5.42, 5.92]
	Naturalness	1.90	0.09	[1.73, 2.08]
	Animal protein	−0.54	0.09	[−0.71, −0.37]
	Energy	−0.22	0.09	[−0.39, −0.05]
	Refined carbs	−0.76	0.07	[−0.90, −0.63]
Adults				
	Intercept	4.41	0.04	[4.33, 4.50]
	Naturalness	2.04	0.02	[2.01, 2.09]
	Animal protein	−1.03	0.02	[−1.08, −0.99]
	Non-sweet carbs	−0.02	0.02	[−0.06, 0.02]
Adolescents				
	Intercept	5.04	0.10	[4.84, 5.24]
	Processing	−1.84	0.08	[−1.97, −1.71]
	Animal protein	−0.52	0.10	[−0.72, −0.33]
	High fiber	−0.17	0.05	[−0.28, −0.07]
	High sugar	−0.37	0.04	[−0.45, −0.29]

Note. 95% CIs are shown in brackets.

Table 3

Core Array Showing the Relationship Between Three Modes and Their Components

	Protein-rich foods				Fruits and vegetables				Processed foods			
Person Component	Silent killers	Modern vices	Healthy diet	Carbs	Silent killers	Modern vices	Healthy diet	Carbs	Silent killers	Modern vices	Healthy diet	Carbs
Processed foods as modern vices	7.60 (−0.18, 14.67)	−0.02 (−4.70, 4.38)	**22.56** (16.05, 27.48)	**−40.85** (−43.66, −36.51)	−13.09 (−20.86, −5.96)	**−24.30** (−30.43, −18.02)	**28.27** (19.12, 33.62)	**31.64** (26.32, 35.01)	0.68 (−0.86, 2.88)	**67.96** (62.66, 72.08)	−6.44 (−9.31, −3.59)	**22.46** (17.53, 26.15)
Processed foods not all that bad	−8.21 (−12.45, −5.07)	2.36 (−1.56, 6.62)	−5.21 (−9.84, −1.92)	−13.72 (−16.99, −10.88)	−15.36 (−21.33, −10.71)	3.17 (−2.38, 9.03)	−3.90 (−10.48, 1.48)	5.65 (1.81, 9.58)	**−109.90** (−110.45, −107.11)	−5.21 (−9.26, −0.35)	−8.39 (−10.92, −6.13)	−9.85 (−14.49, −5.72)
Processed foods as a healthy diet	10.10 (6.20, 13.91)	7.70 (2.49, 13.02)	−1.55 (−7.27, 3.64)	2.20 (−1.44, 6.33)	8.32 (3.99, 13.14)	18.66 (11.10, 25.54)	−2.40 (−10.42, 4.60)	2.71 (−1.57, 6.59)	2.61 (1.34, 4.21)	−7.94 (−13.62, −1.06)	**73.13** (67.92, 74.06)	10.90 (6.00, 14.68)

Note. 95% CIs obtained by bootstrap procedures are shown in parentheses. For better readability, values > 20 are set in boldface.

Figure 1

Biplots showing component loadings and component scores for (a) experts, (b) adults, and (c) adolescents

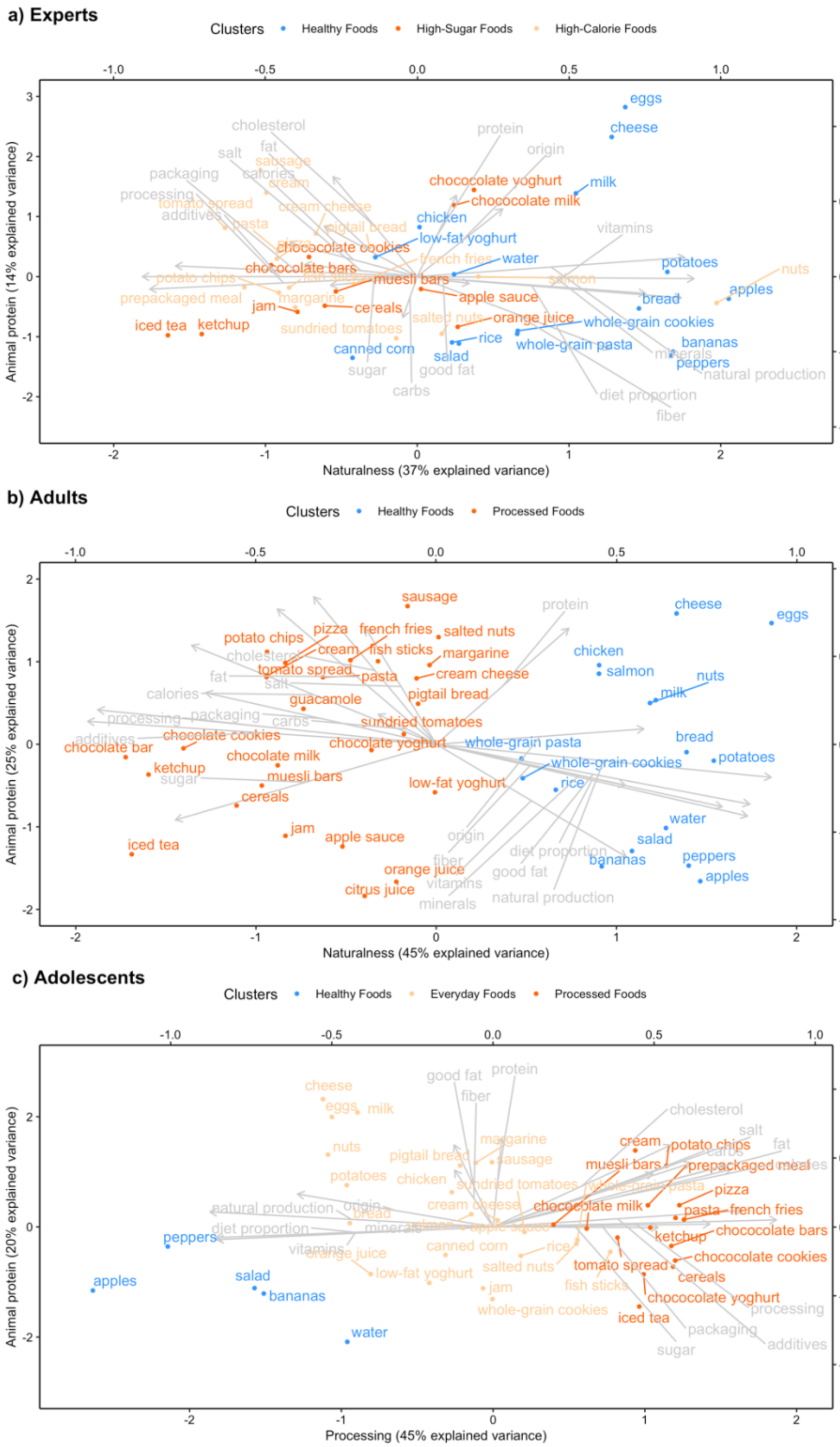
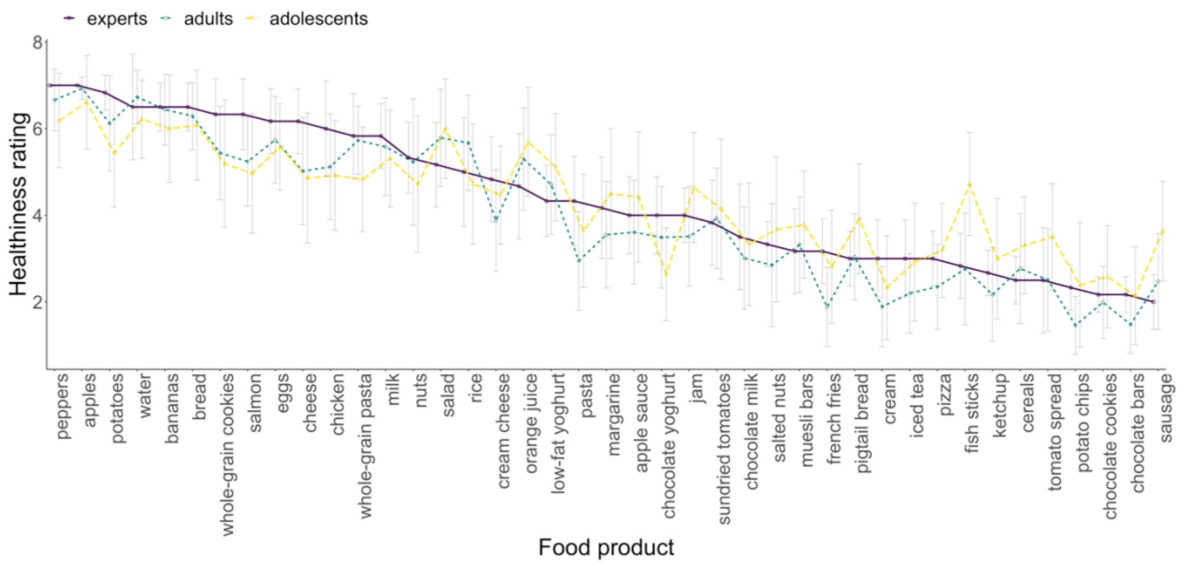


Figure 2

Healthiness ratings for the 41 food products in descending order based on the experts' ratings



Appendix A

Level of Agreement Across the Individual Characteristics and Food Products

To gain insights into which individual food characteristics and food product profiles were best (least) understood by each respondent group, we computed Krippendorff's alpha for each characteristic (e.g., fat/sugar/calorie content, etc., of each of 41 products) and product (e.g., how do apples/bananas/chips, etc., score on all 17 characteristics), separately for each group. The level of agreement within the groups provided us with further indication of which characteristics and products were well/poorly understood and thus require more focus by researchers and educators in the future.

Agreement in Ratings for Individual Characteristics

To assess the similarity in ratings within the respondent groups for the individual characteristics, we computed Krippendorff's alpha using the individual ratings of the 41 food products on the 17 characteristics. This made it possible to assess the level of agreement within each group, and separately for each characteristic, in respondents' ratings of the 41 products. We generated profiles for each characteristic and assessed the level of agreement within each respondent group regarding the profile of each characteristic. The results showed that the experts agreed most strongly on the fat content, recommended proportion of a healthy diet, and salt content; the adults on the recommended proportion of a healthy diet, fat content, and artificial additives; and the adolescents on the recommended proportion of a healthy diet, natural production, and fat content. For a full overview of results, see Table A1.

Agreement in Ratings for Individual Food Products

We next assessed the similarity in ratings for the individual food products within the respondent groups. Here, we were interested in the level of agreement within each group, and separately for each food product, on how, for instance, apples/bananas/ chips etc. scored on all 17 characteristics. The results suggest that the experts agreed most strongly on the profiles of water, apples, and potatoes; the adults on the profiles of water, apples, and chocolate bars; and the adolescents on the profiles of apples, water, and salad. For a full overview of results, see Table A2.

Table A1

Level of Agreement (Indexed by Krippendorff's Alpha) Within Each Respondent Group, Separately for Each Characteristic

	Respondent Group		
Characteristic	Experts	Adults	Adolescents
Fat content	**0.813**	0.647	0.212
Good fat	0.486	0.370	0.005
Sugar content	0.639	0.603	0.180
Vitamin content	0.502	0.446	0.125
Salt content	0.716	0.527	0.110
Protein content	0.707	0.355	0.070
Fiber content	0.714	0.278	−0.003[a]
Mineral content	0.418	0.223	0.027
Calorie content	0.600	0.491	0.127
Cholesterol content	0.556	0.402	0.027
Carbohydrate content	0.700	0.392	0.041
Natural production	0.404	0.353	0.226
Recommended proportion of diet	0.737	**0.666**	**0.282**
Artificial additives	0.557	0.617	0.077
Level of processing	0.596	0.611	0.193
Origin	0.533	0.466	0.082
Level of packaging	0.393	0.433	0.103

Note. The numbers in bold show the characteristic with the highest agreement within the respective respondent group.

[a]Krippendorff's alpha can produce negative values if coders consistently agree to disagree, follow different coding instructions, or have a conflicting understanding of them.

Table A2

Level of Agreement (Indexed by Krippendorff's Alpha) Within Each Respondent Group, Separately for Each Food Product

	Respondent Group		
Food Product	Experts	Adults	Adolescents
Apples	0.825	0.703	**0.426**
Apple sauce	0.667	0.423	0.080
Bananas	0.743	0.615	0.220
Bread	0.618	0.530	0.218
Cereals	0.637	0.456	0.088
Cheese	0.724	0.508	0.191
Chicken	0.593	0.312	0.128
Chocolate bars	0.752	0.684	0.151
Chocolate cookies	0.703	0.634	0.136
Chocolate milk	0.577	0.468	0.094
Chocolate yoghurt	0.575	0.355	0.093
Cream	0.702	0.584	0.156
Cream cheese	0.573	0.363	0.082
Eggs	0.787	0.579	0.254
Fish sticks	0.596	0.456	0.090
French fries	0.546	0.503	0.113
Iced tea	0.733	0.521	0.094
Jam	0.673	0.409	0.147
Ketchup	0.706	0.569	0.071
Low-fat yoghurt	0.544	0.296	0.145
Margarine	0.664	0.375	0.084
Milk	0.639	0.432	0.214

Muesli bars	0.637	0.473	0.071
Nuts	0.623	0.382	0.128
Orange juice	0.631	0.399	0.208
Pasta	0.628	0.528	0.094
Peppers	0.802	0.616	0.354
Sweet yeast bread	0.575	0.369	0.094
Pizza	0.657	0.599	0.097
Potato chips	0.679	0.635	0.138
Potatoes	0.811	0.580	0.219
Rice	0.629	0.435	0.115
Salad	0.751	0.589	0.357
Salmon	0.620	0.330	0.065
Salted nuts	0.612	0.457	0.089
Sausage	0.748	0.521	0.112
Sundried tomatoes	0.438	0.258	0.071
Tomato spread	0.654	0.539	0.093
Water	**0.867**	**0.707**	0.400
Whole-grain cookies	0.494	0.257	0.129
Whole-grain pasta	0.624	0.362	0.076

Note. The numbers in bold show the food product with the highest agreement within the respective respondent group.

Appendix B

Description of the First Six Steps in the 3MPCA

The first step in the 3MPCA was to estimate the variance components to assess whether a three-way analysis was suitable. This would be the case if the data contained a considerable three-way interaction across the three data modes, that is, in our case, if individuals differed in their pattern of responses to the characteristic rating scales for the different food products. If, on the other hand, individuals showed roughly the same pattern of responses to the characteristic rating scales for the different food products, PCA could be used on the aggregated data. Table B1 shows the results of the variance component estimation.

Table B1

Estimated Variance Components and Variance Percentages

Effect	SS	%
Individuals	21239.77	3.94
Characteristics	39569.07	7.34
Food products	8748.52	1.62
Individuals × characteristics	56465.61	10.47
Individuals × food products	22629.57	4.20
Characteristics × food products	194697.89	36.10
Individuals × characteristics × food products	195974.60	36.34
Total	539325.04	100

Note. SS = sum of squares

As Table B1 shows, the data averaged across individuals—which is reflected in the characteristics and food products as main effects and the interaction between the two—explained

45.06% of the variance (7.34% + 1.62% + 36.10%). This means that 54.94% of the variance is related to either individual differences or measurement errors. Although we cannot determine what part of this percentage is attributable to measurement errors, it seems that an important three-way interaction could exist. These results suggest that individuals differ in their pattern of responses to the characteristic rating scales for the different food products on selected food properties, and that a 3MPCA could help to provide insights into those differences.

In the second step, the data were preprocessed. The decision on how to preprocess the data depends on two main factors, namely, whether the neutral points of the rating scales and differences in scale range use among respondents are known. The rating scales in our studies were Likert scales ranging from 1 to 7 with no known neutral points. In addition, the label names of the rating scales differed slightly, meaning that the neutral points may have differed across scales. We therefore decided to eliminate unknown neutral points by centering the data across individuals. Because the label names differed, respondents may have used different scale ranges across rating scales. To eliminate such differences in scale range use, we normalized the data within rating scales.

The third step involves balancing the fit and parsimony of a model in order to choose the optimal number of components to describe the data. We evaluated several models with different numbers of components (minimum two components per mode). For practical reasons (i.e., easier interpretability), we used three components for individuals and four components for characteristic rating-scale and food-product modes as a maximum. We identified the best model using the hull heuristic (Lorenzo-Seva, Timmerman, & Kiers, 2011), which focuses on finding an optimal balance between fit and degrees of freedom. According to this heuristic, the best model had A = 3 (person) components, B = 4 (characteristic) components, C = 3 (food product) components (i.e., 10 components in total) and a value of 2.99 on the scree test. The selected model also seemed to be stable in the split-half procedure (i.e., yielding high congruence values), and it gave relatively small bootstrap confidence intervals for the results of the analysis.

In the fourth step, fit and residuals were studied in more detail. Here we focused solely on fit by inspecting whether each of the B (characteristic) and C (food product) mode entities were fitted well enough. As shown in Tables B2 and B3, the fit percentages were reasonable for most of the characteristics and food products, respectively. Only natural production and packaging (characteristics) and bananas, salad, and water (food products) fitted rather poorly. Increasing the number of components did not improve the fit for these particular entities, so we decided to proceed with the 3-4-3 solution.

The fifth step involves choosing a rotation. We carried out a simple structure rotation with varying weights with the intention of simplifying the B and C modes. We gradually increased the relative weights for B and C from 1 to 5 and concluded that increasing the relative weights beyond 4 made little sense. We therefore decided to proceed with weights of 3 for the B and C modes.

In the sixth step, we studied the stability of the solution by performing split-half analysis. To this end, we randomly split the data into two halves based on the A mode. The congruence values for B mode were 0.99, 0.99, 0.98, and 0.99; those for C mode were 0.98, 0.97, and 1.00, indicating a very stable solution according to the guidelines proposed by ten Berge (1986). Split-half analysis for the core array showed that cores for the two splits were very similar. Comparison of two core splits to the core for the full data showed weaker but sufficient stability.

Tables B2 and B3 show the rotated component matrices for the characteristics (B mode) and food products (C mode), respectively. To assess the validity of the component matrices obtained, we carried out a bootstrap procedure for computing confidence intervals based on 1000 bootstrap samples (Kiers, 2004).

Table B2

Component Values of the "Characteristics" Mode, 95% Confidence Intervals, and Fit Percentages

Item	Silent killers	95% CI		Modern vices	95% CI		Healthy diet	95% CI		Carbs	95% CI		Fit (%)
Fat content (1 = very little)	0.27	0.24	0.30	0.21	0.15	0.27	−0.05	−0.10	0.01	**−0.32**	−0.37	−0.27	18.78
Good fat (1 = very little)	0.29	0.26	0.32	**−0.32**	−0.38	−0.23	−0.08	−0.16	0.02	−0.14	−0.22	−0.07	18.38
Sugar content (1 = very little)	**0.30**	0.27	0.33	−0.15	−0.19	−0.10	−0.19	−0.23	−0.12	**0.30**	0.24	0.35	18.46
Vitamin content (1 = very little)	0.17	0.14	0.20	−0.02	−0.09	0.04	**0.42**	0.37	0.47	0.05	0.00	0.10	21.92
Salt content (1 = very little)	**0.33**	0.29	0.35	0.21	0.15	0.26	0.12	0.06	0.17	−0.20	−0.25	−0.14	22.67
Protein content (1 = very little)	0.27	0.23	0.30	0.04	−0.02	0.09	**0.31**	0.24	0.36	−0.19	−0.25	−0.12	20.77
Fiber content (1 = very little)	**0.36**	0.32	0.38	−0.32	−0.36	−0.28	0.09	0.03	0.14	0.28	0.22	0.32	29.93
Mineral content (1 = very little)	0.18	0.15	0.21	0.16	0.07	0.21	**0.51**	0.43	0.55	0.12	0.08	0.16	30.32
Calorie content (1 = very few)	0.12	0.09	0.16	**0.57**	0.50	0.60	0.12	0.04	0.17	0.05	0.00	0.11	26.14
Cholesterol content (1 = very little)	**0.42**	0.38	0.44	−0.10	−0.17	−0.04	−0.10	−0.17	−0.02	−0.26	−0.31	−0.18	29.06
Carbohydrate content (1 = very little)	0.10	0.08	0.13	0.12	0.06	0.16	0.07	0.02	0.12	**0.71**	0.66	0.75	29.02

Natural production (1 = not naturally produced)	−0.09	−0.14	−0.03	−0.14	−0.23	−0.05	0.24	0.15	0.33	−0.10	−0.14	−0.05	9.07
Recommended proportion of a healthy diet (1 = small proportion)	0.09	0.05	0.12	**−0.38**	−0.42	−0.32	0.16	0.11	0.22	0.02	−0.01	0.06	15.80
Artificial additives (1 = very few)	0.35	0.32	0.38	0.06	0.00	0.12	**−0.37**	−0.41	−0.31	0.09	0.05	0.12	29.58
Level of processing (1 = little processing)	0.07	0.02	0.11	**0.30**	0.24	0.36	−0.16	−0.20	−0.09	0.11	0.07	0.15	12.51
Origin (1 = from a distant country)	−0.11	−0.16	−0.05	−0.06	−0.15	0.03	**0.33**	0.23	0.42	−0.03	−0.08	0.04	11.39
Level of packaging (1 = little packaging)	0.16	0.07	0.23	0.21	0.09	0.31	−0.11	−0.23	0.02	0.02	−0.04	0.07	9.29

Note. The 95% CIs were obtained using bootstrapping. For better readability, absolute values > .3 are set in boldface. Fit percentages indicate how well an individual characteristic is represented.

Table B3

Component Values of the "Food Products" Mode, 95% Confidence Intervals, and Fit Percentages

Item	Protein-rich foods	95% CI		Fruits and vegetables	95% CI		Processed foods	95% CI		Fit (%)
Apples	−0.01	−0.05	0.02	**0.30**	0.23	0.35	0.08	0.07	0.10	15.11
Apple sauce	−0.22	−0.26	−0.18	0.12	0.08	0.16	0.16	0.15	0.18	24.25
Bananas	0.22	0.16	0.26	0.11	0.06	0.15	0.09	0.07	0.10	8.40
Bread	0.07	0.00	0.12	0.25	0.16	0.30	0.12	0.10	0.13	16.10
Cereals	−0.20	−0.23	−0.16	0.02	−0.01	0.06	0.19	0.17	0.20	27.56
Cheese	**0.39**	0.33	0.42	0.00	−0.06	0.03	0.15	0.13	0.16	25.98
Chicken	0.17	0.10	0.22	0.02	−0.03	0.08	0.14	0.12	0.15	13.81
Chocolate bars	−0.20	−0.23	−0.15	−0.09	−0.13	−0.05	0.18	0.16	0.20	27.81

Chocolate cookies	−0.15	−0.18	−0.11	−0.07	−0.10	−0.03	0.19	0.17	0.20	29.06
Chocolate milk	−0.04	−0.10	0.02	0.04	−0.03	0.10	0.18	0.17	0.19	22.50
Chocolate yoghurt	0.05	−0.02	0.10	0.14	0.08	0.18	0.16	0.15	0.18	21.16
Cream	0.11	0.04	0.18	−0.15	−0.20	−0.08	0.18	0.15	0.20	21.06
Cream cheese	0.15	0.11	0.18	−0.18	−0.20	−0.13	0.18	0.17	0.19	30.04
Eggs	**0.33**	0.26	0.36	0.10	0.05	0.12	0.10	0.09	0.11	16.40
Fish sticks	0.05	0.00	0.10	−0.15	−0.19	−0.11	0.18	0.16	0.19	24.26
French fries	−0.07	−0.11	−0.03	0.02	−0.02	0.08	0.18	0.16	0.20	21.87
Iced tea	−0.19	−0.24	−0.11	−0.02	−0.07	0.06	0.16	0.14	0.18	20.94
Jam	−0.21	−0.25	−0.15	0.04	0.00	0.09	0.17	0.15	0.19	24.23
Ketchup	−0.27	−0.30	−0.21	−0.04	−0.08	0.01	0.19	0.17	0.20	28.17
Low-fat yoghurt	−0.01	−0.05	0.03	0.03	−0.02	0.08	0.15	0.13	0.16	15.06
Margarine	0.06	0.00	0.12	−0.18	−0.23	−0.12	0.17	0.16	0.19	20.26
Milk	0.15	0.07	0.19	0.17	0.12	0.20	0.13	0.12	0.15	17.09
Muesli bars	−0.17	−0.20	−0.11	−0.04	−0.08	0.01	0.19	0.17	0.20	28.34
Nuts	0.13	0.05	0.19	0.11	0.03	0.16	0.15	0.13	0.16	13.86
Orange juice	−0.20	−0.24	−0.14	0.09	0.04	0.15	0.18	0.16	0.20	21.72
Pasta	−0.02	−0.06	0.02	−0.11	−0.14	−0.06	0.18	0.16	0.19	24.71
Peppers	0.07	0.01	0.11	0.29	0.23	0.33	0.07	0.06	0.09	12.99
Pigtail bread	−0.07	−0.12	−0.02	−0.05	−0.09	−0.01	0.18	0.16	0.19	22.98
Pizza	−0.05	−0.09	−0.01	−0.15	−0.18	−0.10	0.19	0.17	0.20	29.12
Potato chips	−0.07	−0.11	−0.02	−0.09	−0.14	−0.04	0.18	0.16	0.20	21.96
Potatoes	0.08	0.03	0.10	**0.37**	0.32	0.40	0.11	0.10	0.13	23.26
Rice	−0.05	−0.09	−0.01	0.22	0.17	0.26	0.15	0.13	0.17	21.79
Salad	0.05	−0.03	0.13	0.12	0.06	0.19	0.06	0.04	0.07	3.63
Salmon	**0.32**	0.26	0.36	−0.06	−0.12	−0.01	0.14	0.12	0.15	18.88
Salted nuts	0.10	0.03	0.17	−0.14	−0.20	−0.08	0.16	0.14	0.18	17.22
Sausage	0.17	0.13	0.21	−0.28	−0.31	−0.24	0.17	0.15	0.18	28.02
Sundried tomatoes	0.05	0.00	0.10	−0.09	−0.13	−0.04	0.17	0.15	0.18	19.68
Tomato spread	0.12	0.08	0.15	−0.24	−0.27	−0.20	0.18	0.17	0.19	29.37
Water	0.09	0.01	0.17	0.10	0.03	0.17	0.07	0.05	0.09	6.67
Whole-grain cookies	−0.01	−0.09	0.06	0.14	0.05	0.20	0.15	0.13	0.16	17.00
Whole-grain pasta	−0.02	−0.07	0.02	0.28	0.22	0.32	0.14	0.13	0.15	21.57

Note. The 95% CIs were obtained using bootstrapping. For better readability, absolute values > .3 are set in boldface. Fit percentages indicate how well a food product is represented.