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

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Almost 40% of global mortality is attributable to an unhealthy diet, and adolescents and young adults are particularly affected by growing obesity rates. How do (young) people conceptualize and judge the *healthiness of foods* and how are the judgments embedded in people's mental representations of the food ecology? We asked respondents to rate a large range of common food products on a diverse set of characteristics and then applied the psychometric paradigm to identify the dimensions structuring people's mental representations of the foods. Respondents were also asked to rate each food in terms of its healthiness, and we used the foods' scores on the extracted dimensions to predict the healthiness judgments. We compared three groups of respondents: adolescents, lay adults, and nutrition experts. Naturalness levels (e.g., processing, artificial additives) and cholesterol and protein content emerged as the two central dimensions structuring respondents' mental representations of the foods. Relative to the other two groups, the adolescents' representations were less differentiated. Judged food healthiness was determined by multiple factors, but naturalness was the strongest predictor across all groups. Overall, the adolescents' responses showed considerable heterogeneity, suggesting a lack of solid food knowledge and the need for tailored nutrition education on specific food products and content characteristics.

Public Significance Statement
This study examines mental representations of foods and how these guide how "healthy" people judge these foods to be, comparing adolescents, adults, and experts. The results show that for all respondents, perceived naturalness is a central dimension underlying mental representations of foods and the strongest predictor of healthiness judgments. Compared to experts and adults, adolescents exhibit the greatest variability in their food assessments, indicating a lack of solid food knowledge.

Keywords: healthiness judgments, mental representation, psychometric paradigm, individual differences, food choice

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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 et al., 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" (World Health Organization [WHO], 2015, p .4).

But, how do people intuitively conceptualize and judge *healthy* foods? Given that laypeople often have only limited knowledge of the healthiness of food (e.g., Hendrie et al., 2008), numerous food labels (e.g., the traffic light scheme in the U.K. 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, although some labels or health claims affect people's judgments of food healthiness, this is not always the case (Lähteenmäki, 2013; Orquin, 2014). These findings suggest that "quick fix" solutions like these are not effective (but, see Trudel et al., 2015). An alternative approach is first to understand better how people mentally 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 et al., 2020). The present research

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adopts this approach using a wide variety of food products and content characteristics to identify the structures underlying people's perception of the food ecology and how these structures are connected to people's healthiness judgments.

As delineated in the next section, 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 instead (a) consider a large and heterogeneous set of food products, (b) use a bottom-up approach to identify the factors that structure people's mental representations of food products, and (c) examine how these structures are linked to subjective perceptions of food healthiness. A key contribution of our research is that to map people's mental representations of food products and judgments of food healthiness, we employ the psychometric paradigm—a methodological approach that was pioneered in research on risk perception to identify key dimensions underlying subjective representations of hazards (Fischhoff et al., 1978; Slovic, 1987). To our knowledge, with the exception of Bucher et al. (2016), this approach has not previously been applied to the perception of foods. To contextualize the results, we compare findings for laypeople (i.e., adults and adolescents) and nutrition experts; to trace possible developmental differences in the perception of food products, 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 et al., 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 a food have an important influence on judgments of food healthiness, and that these cues may also interact with other cues. For instance, Oakes and Slotterback (2002) showed that fat content (along with freshness) was the most important characteristic when respondents judged the healthiness of various foods. 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 impacts people's perceptions of healthy eating.

Further support for the importance of specific nutrients on judgments of food healthiness comes from Nielsen et al. (1997), who found that level of processing, vitamin and mineral content, and fat percentage emerged as important factors contributing to the subjective healthiness of fish. Similarly, Bech-Larsen (2001) focused on apples and found that vitamin contents as well as the descriptors "organic" and "wholesome" were the strongest predictors of healthiness judgments in this context. Nielsen et al. (1998) studied the perception of 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 assessed 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 6 food characteristics, Bucher et al. (2015) found that fruit/vegetable and fiber content were associated with higher judged healthiness, whereas sugar and fat content were linked to lower judged healthiness.

Note that although this research has produced valuable insights concerning the specific properties of nutritional content that contribute to the perceptions of food healthiness, some studies relied on only one product type (e.g., Bech-Larsen, 2001; Nielsen et al., 1997, 1998) and most looked at only a small set (i.e., three to seven) of food characteristics (for an overview of relevant studies, see Table S1 in the Supplemental Material). 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 subjective 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 et al. (2012) reported that a fair-trade label—which denotes better trading conditions for producers—evoked higher perceived healthiness.

Product Features

Finally, also 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 subjective food 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) reported that products in matte packages were judged as healthier than products in glossy packages. Haws et al. (2017) explored the relationship between price and perceived healthiness, and observed 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 use by product designers 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 judgments of food healthiness are likely to 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 raw foods (e.g., broccoli, pumpkin) as good or bad, they struggle when classifying transformed foods or foods that combine multiple ingredients (e.g., pasta with broccoli and cheese; Gosling et al., 2008; Thompson et al., 2011). In addition, young children 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).

Judgments 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 et al., 2012). In a study with a large, nationwide U.S. sample that included the respondents of various ages, Lusk (2019) found evidence (using exploratory factor analysis) that perceived healthiness is based on at least three latent dimensions: animal origin, preservation, and freshness/processing. Nutrients such as fat, sodium, carbohydrate, and protein content also affect judged healthiness, 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., the presence of additives) to gauge food healthiness. In summary, the perception of food healthiness seems to become more nuanced from childhood to adolescence, and the perception in adolescents resembles that of adults.

Interim Summary and Rationale for the Present Research

Previous research has identified a wide range of characteristics that influence judgments 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 subjective healthiness seems to undergo differentiation over ontogenetic development, the most pronounced changes occur between childhood and adolescence, with little evidence for further differentiation in adulthood. The previous studies, however, have mainly focused on a fairly limited set of food characteristics and studied homogeneous samples. It is therefore unclear to what extent findings hold for the perception of food healthiness more generally. To effectively tackle growing obesity rates and the associated NCDs, policymakers need to implement measures informed by a well-founded understanding of how the general public mentally represents a broad range of common food products in terms of many characteristics. Toward that goal, we applied the *psychometric paradigm* (see below for details) to assess people's mental representation of a broad range of common food products, each assessed on a diverse set of food characteristics. Our aim was to identify a number of overarching structures underlying people's representation of the food ecology and to test how these structuring dimensions of food perceptions are associated with the products' perceived healthiness.

We employed the psychometric paradigm to compare the food perception of adolescents, lay adults, and nutrition experts. We focused on adolescents and younger adults because adolescence and younger adulthood 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 et al., 1988; Poobalan et al., 2014). We deliberately did not include preadolescent 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). Our inclusion of nutrition experts further enabled us to contextualize the results by comparing and contrasting the findings for two distinct groups of laypeople with a group whose representational structures should constitute an approximate normative standard.

Based on the existing work reviewed in the previous section, it may be expected that adolescents and lay adults will largely be aligned with respect to their overall judgments of food healthiness. However, lay adults should reasonably exhibit a more fine-grained view of the food ecology, whereas adolescents may be more prone to display a polarized representation, consistent with a good–bad dichotomy. Furthermore, nutrition experts will arguably make the most detailed distinctions between food products. 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 laypeople'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 "mental 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 (see also Waters et al., 2017).

The typical setup of the psychometric paradigm 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. 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 mental 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 et al., 2012; Slovic et al., 1985; see also Waters et al., 2017). The same approach has been used to compare the risk perceptions of laypeople and experts (e.g., Slovic et al., 1981).

Overview of the Study

Our study had four main goals. First, based on the 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 mental representations of food products based on people's ratings of the foods on a broad range of characteristics. 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). Fourth and finally, we examined differences in the ratings and mental representations of the 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 the 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. All respondents received a compensation of 20 Swiss Francs for their participation.

Materials and Procedure

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 chain) and asked "How healthy is this food product?" Responses for each product were given on a 7-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 nonoverlapping products were not included in the analyses, which were based on 41 food products. A list of all food products is provided in Appendix B (Table B2).

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 7-point Likert scale, with labels differing slightly depending on the characteristic. For instance, for "fat content," we asked respondents, "Does the food product contain a lot of fat?" and the scale ranged from 1 = *very little* to 7 = *very much*. For "level of processing," we asked respondents, "Is the food product heavily processed or more natural?" and the scale ranged from 1 = *little processed* to 7 = *heavily processed*. 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.

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. The order in which the food products and the characteristics were presented was randomized across respondents. All groups took around 60 min, 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.

[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.

Results

We first examined the main dimensions underlying each group's mental representation of the food ecology. To this end, we conducted a PCA on the average 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. To be able to identify possible differences between the experts, adults, and adolescents, we conducted a separate PCA for each group. Next, we analyzed and compared the healthiness judgments of the three groups and used the food product scores on the dimensions extracted with the PCA to predict respondents' healthiness judgments. Finally, we examined individual differences in the perceptions of the foods and analyzed individual differences in respondents' mental representations of food products by performing a three-way PCA (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 Kaiser criterion (i.e., the requirement of eigenvalues being larger than 1) and the "elbow" criterion (i.e., the point in the scree plot where the eigenvalues of additional components level off), we retained four components for the expert and adolescent groups, and three components for the adult group. We used varimax (adults and experts) and quartimax (adolescents) rotations to facilitate the interpretation of the solutions. Table 1 shows how the individual characteristics loaded on the resulting principal components (PCs) for each respondent group.

As shown in Table 1, all PCs together explained 80% of the total variance both for the experts and adults, and 83% for the adolescents. What are the dimensions extracted by the PCA? Starting with the experts, the characteristics mineral content, natural production, and vitamin content had the highest positive loadings on the first PC, while artificial additives and level of processing had the highest negative loadings. We therefore labeled this component "naturalness." The second PC had the highest loadings for cholesterol and protein content, so we labeled this component "cholesterol and protein." The third PC had the highest loadings for good fat, fat content, and calorie content, so we labeled it "energy." The fourth PC had the highest loadings for sugar content and carbohydrate content, so we labeled it "bad carbs."

In the adult group, the characteristics natural production, good fat, 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 labeled that component "naturalness." Cholesterol, fat, salt, and protein content had the highest loadings on the second PC, which we labeled

Table 1
Loadings of the 17 Characteristics on the Principal Component Analysis Solutions by Respondent Group

	Experts				Adults			Adolescents			
Characteristic	Naturalness	Cholesterol and protein	Energy	Bad carbs	Naturalness	Cholesterol and protein	Good carbs	Processing	Fat and protein	High fiber	Sweet versus salty
Artificial additives	**−0.90**	−0.02	0.14	0.26	**−0.98**	0.02	0.01	**0.89**	−0.06	0.12	0.21
Calorie content	−0.44	0.27	**0.71**	0.42	**−0.73**	0.50	0.30	**0.90**	0.32	0.05	0.04
Carbohydrate content	−0.02	−0.30	−0.05	**0.81**	−0.14	0.12	**0.89**	**0.79**	0.39	0.17	−0.08
Cholesterol content	−0.30	**0.83**	0.24	−0.17	−0.47	**0.84**	−0.05	**0.74**	0.58	0.05	−0.14
Fat content	−0.33	0.41	**0.77**	−0.05	−0.55	**0.74**	0.13	**0.88**	0.36	0.03	−0.03
Fiber content	**0.68**	−0.55	0.09	0.05	0.60	−0.21	**0.72**	0.06	0.41	**0.79**	0.05
Good fat	0.17	−0.05	**0.85**	−0.21	**0.93**	−0.22	0.01	0.08	**0.65**	0.40	−0.18
Level of packaging	**−0.79**	0.12	0.08	−0.06	**−0.69**	0.23	−0.16	**0.63**	−0.02	−0.52	−0.11
Level of processing	**−0.87**	−0.12	0.28	0.25	**−0.95**	0.08	0.11	**0.94**	−0.18	0.04	−0.05
Mineral content	**0.92**	0.02	−0.10	−0.11	**0.83**	−0.26	−0.13	−0.37	0.27	**−0.69**	0.17
Natural production	**0.87**	0.17	−0.19	−0.25	**0.94**	−0.08	−0.12	**−0.90**	0.36	0.05	−0.10
Local origin	0.23	**0.53**	−0.47	−0.11	**0.52**	0.14	−0.39	−0.56	**0.56**	−0.16	0.20
Protein content	0.15	**0.74**	0.27	−0.17	0.26	**0.75**	−0.19	0.17	**0.78**	0.01	−0.16
Recommended proportion of a healthy diet	**0.77**	−0.11	−0.43	−0.35	**0.91**	−0.31	−0.05	**−0.95**	0.13	−0.04	−0.09
Salt content	−0.32	0.15	**0.65**	−0.2	−0.25	**0.66**	0.43	0.55	0.28	0.11	**−0.71**
Sugar content	−0.31	−0.09	−0.21	**0.82**	**−0.67**	−0.53	0.02	0.64	−0.09	0.04	**0.72**
Vitamin content	**0.87**	−0.14	−0.02	0.08	**0.66**	−0.56	0.04	**−0.86**	0.04	0.31	0.24
Eigenvalues	6.31	2.28	2.99	2.00	8.31	3.45	1.86	8.49	2.60	1.71	1.31
Proportion of explained variance	0.37	0.13	0.18	0.12	0.49	0.20	0.11	0.50	0.15	0.10	0.08
Total variance explained (%)		80				80			83		

Note. Loadings in bold represent the highest absolute loading for a specific characteristic for each respondent group. All food characteristics were rated on a Likert scale ranging from 1 to 7. The characteristics "artificial additives," "calorie content," and "vitamin content" were rated on a scale ranging from 1 = *very few* to 7 = *many*; the characteristics "carbohydrate content," "cholesterol content," "fat content," "fiber content," "good fat," "mineral content," "protein content," "salt content," and "sugar content" were rated on a scale ranging from 1 = *very little* to 7 = *very much*; the characteristic "level of packaging" was rated on a scale ranging from 1 = *little packaging* to 7 = *a lot of packaging*; the characteristic "level of processing" was rated on a scale ranging from 1 = *little processed* to 7 = *heavily processed*; the characteristic "natural production" was rated on a scale ranging from 1 = *not naturally produced* to 7 = *naturally produced*; the characteristic "local origin" was rated on a scale ranging from 1 = *from a distant country* to 7 = *from a nearby country*; the characteristic "recommended proportion of a healthy diet" was rated on a scale ranging from 1 = *small proportion* to 7 = *large proportion.*

"cholesterol and protein." Carbohydrates and fiber content had the highest loadings on the third PC, which we labeled "good carbs."

In the adolescent group, the characteristics level of processing, calorie content, and artificial additives had the highest positive loadings on the first PC, while recommended proportion of diet and natural production had the highest negative loadings; we therefore labeled it "processing" (note that most of the same characteristics load on this component as on the "naturalness" component for the other two groups, just with the reversed sign). Protein, good fat, and local origin had the highest loadings on the second PC, which we named "fat and protein." Fiber content (positive) and minerals (negative) had the highest loadings for the third PC, which we labeled "high fiber." Finally, sugar content had the highest positive and salt content had the highest negative loading on the fourth PC, which we labeled "sweet vs. salty."

We used biplots (created with the ggplot function from the ggplot2 package in R; Wickham, 2016) to display 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 variability across the food products on the respective characteristic, and the cosines of the angles between the vectors indicate the correlations between the characteristics (angle $< 90°$ = positive correlation, $90°$ = no correlation, angle $> 90°$ = negative correlation). Furthermore, we identified the clusters of food products for each respondent group using the NbClust function from the NbClust package (Charrad et al., 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 mental representation of the respective respondent group. In the following, we focus on the clustering of foods.

As shown in Figure 1A, for the experts there were three clusters of food products. 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, suggesting two main clusters of food products for this respondent group. One cluster contained 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). The other clusters were products that were 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. Three clusters of food products emerged from their ratings. As for the experts and adults, one cluster distinguished food products that undergo little or no processing, are high in micronutrients, and are 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' mental representations diverge from those of the two other groups. The third cluster is again similar to the clusters identified for the 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).

Taken together, the results of the PCA indicate substantial commonality in mental 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 nutrients such as cholesterol, protein, and fat. 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' 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: Food products with a negative connotation (e.g., chocolate cookies, French fries) cluster together, as do food products with a positive connotation (e.g., apples, peppers).

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 shown, the adolescents' and adults' ratings are generally aligned with the aggregate assessments 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, $r_s = .81$, 95% confidence interval (CI) [0.73, 0.87]; for the adolescents it was somewhat lower, $r_s = .63$, 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 mental representations of the food products identified by 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 et al., 2018) in R. These results, which we discuss in detail shortly, are shown in Table 2. In contrast to the analyses shown 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 PC scores

[2] In the analysis, we set the minimum and maximum number of clusters to 2 and 10, 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).

Figure 1

Biplots Showing the Foods' Component Scores and Component Loadings and for (a) Experts, (b) Adults, and (c) Adolescents

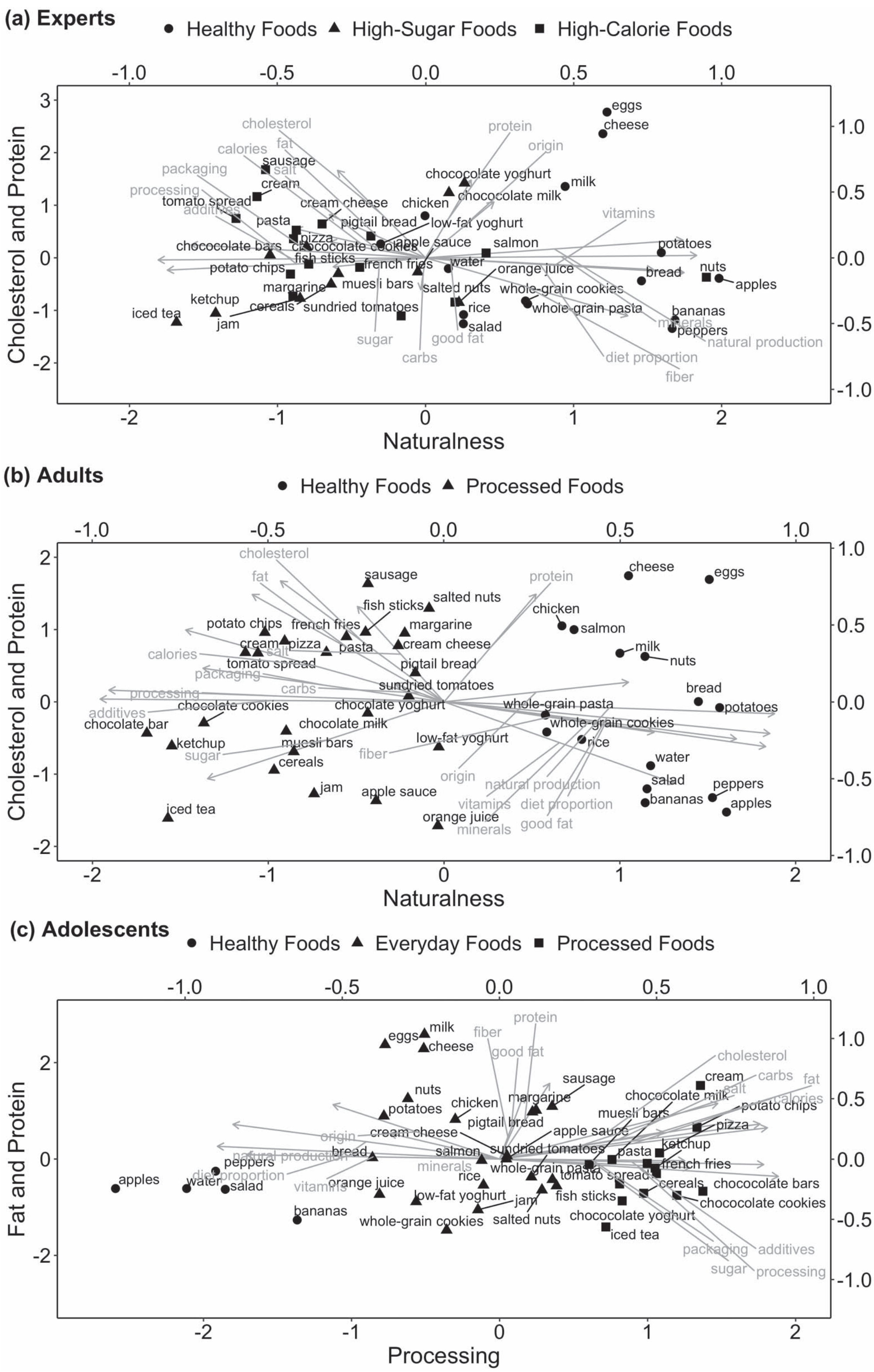
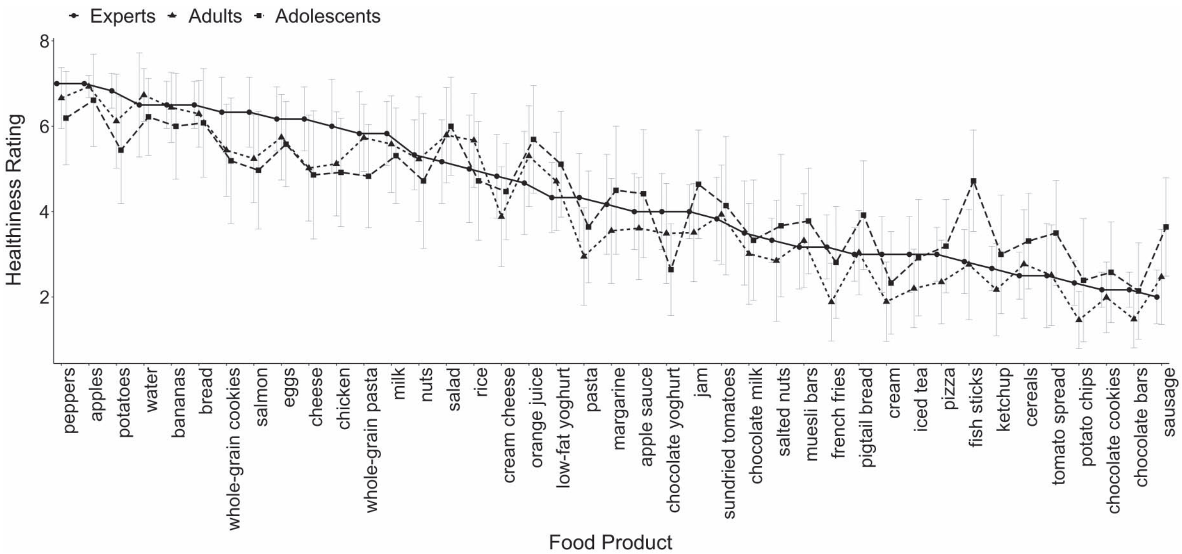


Figure 2

Healthiness Ratings for the 41 Food Products in Descending Order Based on the Experts' Ratings



of each food product served as the independent variable; we included random intercepts for respondents and for food products. To compute a component score for each food product and for each respondent, we used the pseudoinverse 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 shown in Table 2, the experts' healthiness judgments were associated with all four components. "Naturalness" was positively associated with judged healthiness, whereas "cholesterol and protein," "energy," and "bad carbs" were negatively associated (note, however, that "cholesterol and protein" was only marginally associated). In other words, the experts viewed foods as healthier

Table 2

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

Respondent group	Term	Estimate	*SE*	*t* value	95% CI
Experts					
	Intercept	4.66	0.13	36.73	[4.41, 4.91]
	Naturalness	1.92	0.09	21.71	[1.75, 2.10]
	Cholesterol and protein	−0.17	0.09	−1.91	[−0.35, 0.01]
	Energy	−0.55	0.09	−6.09	[−0.72, −0.37]
	Bad carbs	−0.74	0.07	−10.78	[−0.88, −0.61]
Adults					
	Intercept	4.41	0.04	100.45	[4.32, 4.50]
	Naturalness	2.18	0.02	101.69	[2.13, 2.22]
	Cholesterol and protein	−0.74	0.02	−34.54	[−0.78, −0.70]
	Good carbs	−0.17	0.02	−7.91	[−0.21, −0.13]
Adolescents					
	Intercept	4.03	0.10	40.06	[3.83, 4.23]
	Processing	−1.97	0.08	−24.46	[−2.13, −1.81]
	Fat and protein	−0.12	0.10	−1.25	[−0.31, 0.07]
	High fiber	0.06	0.06	1.01	[−0.05, 0.16]
	Sweet versus salty	−0.11	0.04	−2.50	[−0.19, −0.02]

Note. The 95% confidence intervals are shown in brackets. Experts: number of observations = 246, BIC = 731.42, log likelihood = −343.77, standard deviation (random intercept: respondent) = 0.26, standard deviation (random intercept: food product) = 0.88; adults: number of observations = 4,100, BIC = 12007.56, log likelihood = −5974.67, standard deviation (random intercept: respondent) = 0.41, standard deviation (random intercept: food product) = 0.94; adolescents: number of observations = 1,476, BIC = 5186.72, log likelihood = −2564.19, standard deviation (random intercept: respondent) = 0.56, standard deviation (random intercept: food product) = 1.24. BIC = Bayesian information criterion.

if they scored higher on mineral content and natural production ("naturalness") and lower on cholesterol and protein content ("cholesterol and protein"), good fat, fat and calorie content ("energy"), and sugar and carbohydrate content ("bad carbs").

Adults

All three components showed an association with adults' healthiness judgments, namely, "naturalness," "cholesterol and protein," and "good carbs." As for the experts, the association with "naturalness" was positive, indicating here that foods scoring higher on natural production, good fat, and considered part of a healthy diet were judged as healthier. The association with "cholesterol and protein" as well as "good carbs" was negative, indicating that foods scoring low on cholesterol, fat, protein, and salt content ("cholesterol and protein") and carbohydrate content ("good carbs") were judged as healthier.

Adolescents

The healthiness judgments of the adolescents were associated with only two components. Foods scoring lower on the level of processing and artificial additives ("processing") and sugar content ("sweet vs. salty") were judged as healthier.

In summary, the analysis provided insights into the healthiness judgments of the three respondent groups' and how the mental representation of the foods is linked to these judgments of these three groups. 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 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' mental 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 (i.e., low naturalness). In addition, both experts and adolescents rated foods high in sugar to be low in healthiness, whereas both experts and adults perceived foods containing specific nutrients (e.g., cholesterol) to be low in healthiness. The experts', adults', and adolescents' healthiness judgments were associated to four, three, and two of the identified PCs, respectively; this may suggest that the experts were sensitive to a broader range of aspects in their mental representation of the food products to assess their healthiness, relative to the two lay groups.

Level of Agreement in the Food Product Ratings

Although adults' and adolescents' representations of the food ecology were similar to those of the experts in many respects, there was substantially more variability among the adolescents. To quantify the variability across individuals within each group, we computed Krippendorff's α coefficient (Krippendorff, 2011) for the individual-level ratings of the food products on the 17 characteristics. Krippendorff's α 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 α; 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 α.

To compute a Krippendorff's α 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 B.

The analyses thus underline 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 nonaggregated data into account when extracting the key dimensions underlying people's perception of the 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 3MPCA (for details, see Kiers & Van Mechelen, 2001), which enabled us to analyze the nonaggregated 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 these three "modes," making it possible to assess which structures differentiate the elements in each mode.

We conducted the 3MPCA using the ThreeWay package (Giordani et al., 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 C. 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 "characteristics" mode is closest to that analyzed by the PCA. The first component of this mode had the highest component values

Table 3

Core Array Showing the Relationship Between Three Modes and Their Components

Person component	Protein-rich foods				Fruits and vegetables				Processed foods			
	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. The 95% CIs obtained by bootstrap procedures are shown in brakets. For better readability, values >|20| are set in boldface.

for cholesterol, salt, sugar and fiber content.[3] We labeled this component "silent killers" because excessive consumption of foods high in those contents contributes to NCDs (e.g., diabetes, cardiovascular disease, etc.). The second component had the highest component values for calorie content and level of processing. We labeled 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 local origin. We labeled this component "healthy diet." The fourth component had the highest component values for carbohydrate content and was labeled "carbs." For details on this mode and its components, see Table C2.

Comparing these results with those obtained with the PCA shows a number of similarities: The "silent killers" component is similar to the "cholesterol and 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 "bad carbs" and "good 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 labeled "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 cutoff value of .3 (see Table C3). We labeled this component "processed foods."

In some sense, the "food products" mode can be related to the clusters of food products identified in the biplots (Figure 1). 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. In addition, 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

[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).

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 labeled 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 labeled 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 labeled 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.

To summarize, the 3MPCA, which acknowledges individual differences in respondents' mental representations of processed foods, identified differences between groups that were not visible with 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 did, and the adolescents considered processed foods as "part of a healthy diet" to a greater extent than the experts or the adults did.

Discussion

How do people structure their representation of the food ecology? And how are the structures in this mental representation related to how healthy people judge different food products? Using the psychometric paradigm, we identified key dimensions underlying people's perceptions of the food ecology and the (dis)similarities in their healthiness judgments. By comparing adolescents and adults with a benchmark group of nutrition experts using the same study material, adults and adolescents were found to rely on similar dimensions as experts to differentiate food products, especially regarding sugar and carbohydrate content, but also regarding the level of processing involved and perceived naturalness. However, compared to adults, the mental representations of adolescents diverged more from those held by experts, suggesting that knowledge and experience impact people's perceptions of the food ecology. Specifically, adolescents had less differentiated representations and showed a greater tendency to cluster food products and characteristics together, with more polarized perceptions suggestive of a simple good–bad dichotomy. These results indicate that adolescents generally may not (yet) be able to make the same nuanced, fine-grained distinctions between food products as experts and, to some extent, adults.

Regarding healthiness judgments, all groups were generally in agreement. However, the adolescents were again less similar to the experts than 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, perceived naturalness of a food product emerged as the strongest predictor of healthiness judgments in all three respondent groups. This analysis also indicated that the experts considered a larger range of aspects of their mental representations of foods when judging food healthiness, relative to the other two groups. The 3MPCA revealed that whereas experts and adults perceived processed foods as modern vices, adolescents were more inclined to view such foods as part of a healthy diet.

Contributions for Theory and Methodology

Our study makes several contributions. First, we applied the psychometric paradigm to identify the key dimensions that structure people's mental representations of the food ecology. Our results thus offer novel insights with respect to how the food ecology is mentally represented (but, see Bucher et al., 2016). The key dimension that emerged for all three respondent groups can be best described as naturalness of food products, and it was the strongest predictor of respondents' healthiness judgments. Moreover, our approach enabled us to better understand the main characteristics behind this dimension. Specifically, respondents considered naturalness as a property of foods that are little processed, contain few artificial additives (if any), and are rich in vitamins. These insights will be important for future theoretical approaches on the mechanisms underlying the perception of foods and the construction of healthiness judgments.

Second, being based on a diverse set of food products and relevant characteristics, our results offer a more generalizable understanding of the link between mental representations of the food ecology and healthiness judgments than has been the case in much previous research. Prior literature has often used a top-down approach in which people's healthiness judgments of foods have been compared to and matched with predetermined criteria, such as nutrient profile scores (e.g., Bucher et al., 2015) or objective content characteristics available on nutritional labels or through manufacturers (e.g., Rizk & Treat, 2014). Moreover, previous research has frequently focused on a relatively narrow set of content characteristics, commonly in the range of three to seven characteristics (e.g., Oakes & Slotterback, 2001a, b), with several studies also being restricted to healthiness judgments for a single product (e.g., Bech-Larsen, 2001) or product category (e.g., Nielsen et al., 1998) or for foods generally, without specifying the particular type of food (Oakes & Slotterback, 2002). Instead of using predetermined criteria stemming from a top-down approach, we instead relied on a bottom-up approach in which our PCA results served as a guide for drawing inferences about people's healthiness judgments across a multitude of food products and content characteristics. Thus, our approach offers a complementary view on the key dimensions underlying people's perceptions of the food ecology.

Finally, our comparison of adolescents, lay adults, and experts 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. To our knowledge, our investigation is the first to compare laypeople of different ages with experts in terms of their mental representations of the 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.

Practical Implications

Several implications for public policy, marketing, and nutrition education can be derived from our findings. Communication campaigns intended to promote public health may benefit from specifically tailoring their message to the age of their target group in question, rather than using a uniform approach (cf., Ares et al., 2021; Stämpfli et al., 2017; Stöckli & Dorn, 2021). Similarly, marketers, advertisers, and brand owners can draw on the present results to strategically signal healthiness on product packaging, ads, and in-store displays to steer people's choices toward healthier food alternatives. Specifically, our results indicate that the naturalness of a food product is an important dimension of people's mental representation of the food ecology and a key attribute for judgments of food healthiness. To some extent, the same applies to sugar content. Communication campaigns used for public health purposes should therefore emphasize 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 (Cowan, 2020; for another food-related imagery effect, see Christian et al., 2016).

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 B show—there were large individual differences in the adolescents' ratings of cholesterol content, good fat, and carbohydrate content. Similarly, all age groups showed a high level of agreement in their ratings of apples, consistent with the "apple a day" maxim and prior research (e.g., Bucher et al., 2016), but low 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, nutrition educators would be well advised to strategically target those specific 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; World Health Organization, 2017). Health literacy and 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 well-being among people.

Limitations and Future Research

We should acknowledge some potential limitations of our findings. First, the sizes of our samples differed across respondent groups; as such, the differences in factor structures obtained may, to some extent, be due to differences in the reliability of these factor structures across the groups. In addition, the sample size for our group of adolescents was modest ($N = 36$). To examine the robustness of our results as a function of sample size, we conducted two additional analyses (for details about these additional analyses, see Appendix A). One analysis investigated to what extent the PCA results are sensitive when the number of respondents is reduced (relative to when the full sample size for each respondent group is used); the other analysis tested (via computer simulations) the recoverability of correlations between aggregated attribute values—the basis of the PCA—as a function of the sample size on which each attribute value is based. Both analyses suggested that the sample sizes of all our respondent groups were sufficiently large to produce reliable results.

A second caveat is the rather low number of experts for whom healthiness ratings were available, so perhaps the results involving the ratings for this group should be taken with some caution. At the same time, given the high level of consensus in the other ratings of the experts, this concern might not be too critical. Third, the proportion of female respondents differed across groups, which may have influenced the results. However, it should be noted that although some gender differences have been observed, they are typically small (Oakes & Slotterback, 2001a, 2001b) and often not evident at all (Bucher et al., 2016; Oakes & Slotterback, 2002); this suggests that gender differences are 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. In general, the current work provides an important proof-of-concept demonstration of how the psychometric paradigm can be used to analyze people's mental representation of the food ecology and how the representations of different respondent groups can be compared and evaluated against a normative benchmark. As with any single study, however, it will be important in future research to examine the generality of our results in different samples.

Conclusion

Our findings show that judged healthiness of food products is a multifaceted construct that has systematic links to people's representations of the food ecology. It is driven, in part, by more peripheral aspects, such as the level of processing, but also by the proportion of specific nutrients contained in the food, such as cholesterol, fat, and protein content. These structures are already apparent 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.

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Appendix A

Assessing the Robustness of the Results

Robustness of the PCA Solutions

The aim of this analysis was to investigate how robust the PCA results are depending on sample size. Specifically, we reran the analysis reported in the section "What Dimensions Underlie Respondents' Perception of the Food Products" with decreasingly smaller sample sizes, drawn randomly (without replacement) from our data, and checked to what extent the obtained solution matches that using full sample sizes for each respondent group. The solution obtained using a smaller sample size needed to match the one using a full sample size based on two conditions to count as "robust": (a) the highest absolute loading of each food characteristic needed to be the same and (b) the highest absolute loading of each food characteristic needed to load on the same principal component. For each of the 17 food characteristics, we then checked whether both of these conditions were met and computed the percentage of match between the PCA solutions produced by the full and reduced data sets (in terms of sample size). We iterated this process 1,000 times and determined the average of all iterations, and we did this for all respondent groups starting from the N-1 sample size (N = total sample size) and reducing the sample by one respondent at a time until there was only one respondent left.

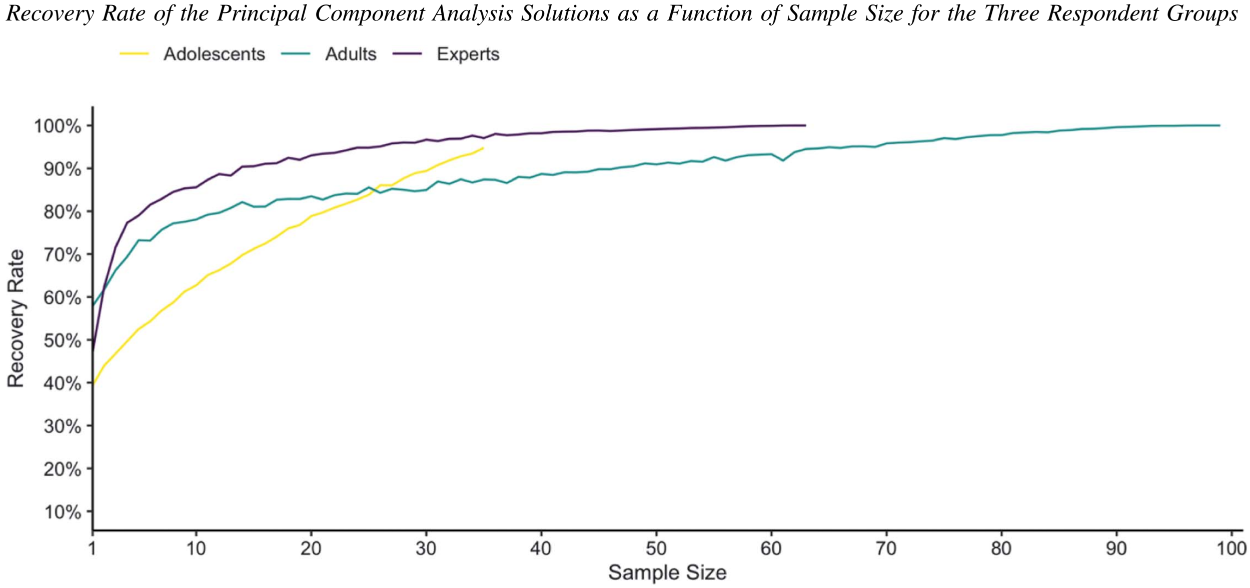
Figure A1 shows how the percentage of match (in the figure this is referred to as "Recovery rate") changes as a function of sample size. In general, the figure shows that even with smaller sample sizes we could replicate our PCA results for all respondent groups. For instance, reducing the sample size by 80% for the expert group produced a match of 90% (recovery rate) with the solution for the full sample; reducing the sample size for the adults group by 55% produced a match of 90%; and reducing the sample size by approximately 40% for the adolescent group produced a match of around 80%. Note that the differences in recovery rate between the respondent groups likely reflect the level of heterogeneity of the responses in the different groups (that we had analyzed with Krippendorff's α): The experts were the most unanimous group and so reducing the sample size even by 80% produced a 90% match with the solution for the full sample, whereas for the adolescents, which showed a considerable level of heterogeneity, the results were less (but still sufficiently) robust when the sample size was reduced.

Recovery of Correlations Based on Aggregated Data Points Under Different Sample Sizes

In a second simulation we examined the more general question of how well correlations between 41 pairs of data points can be

Figure A1

Recovery Rate of the Principal Component Analysis Solutions as a Function of Sample Size for the Three Respondent Groups

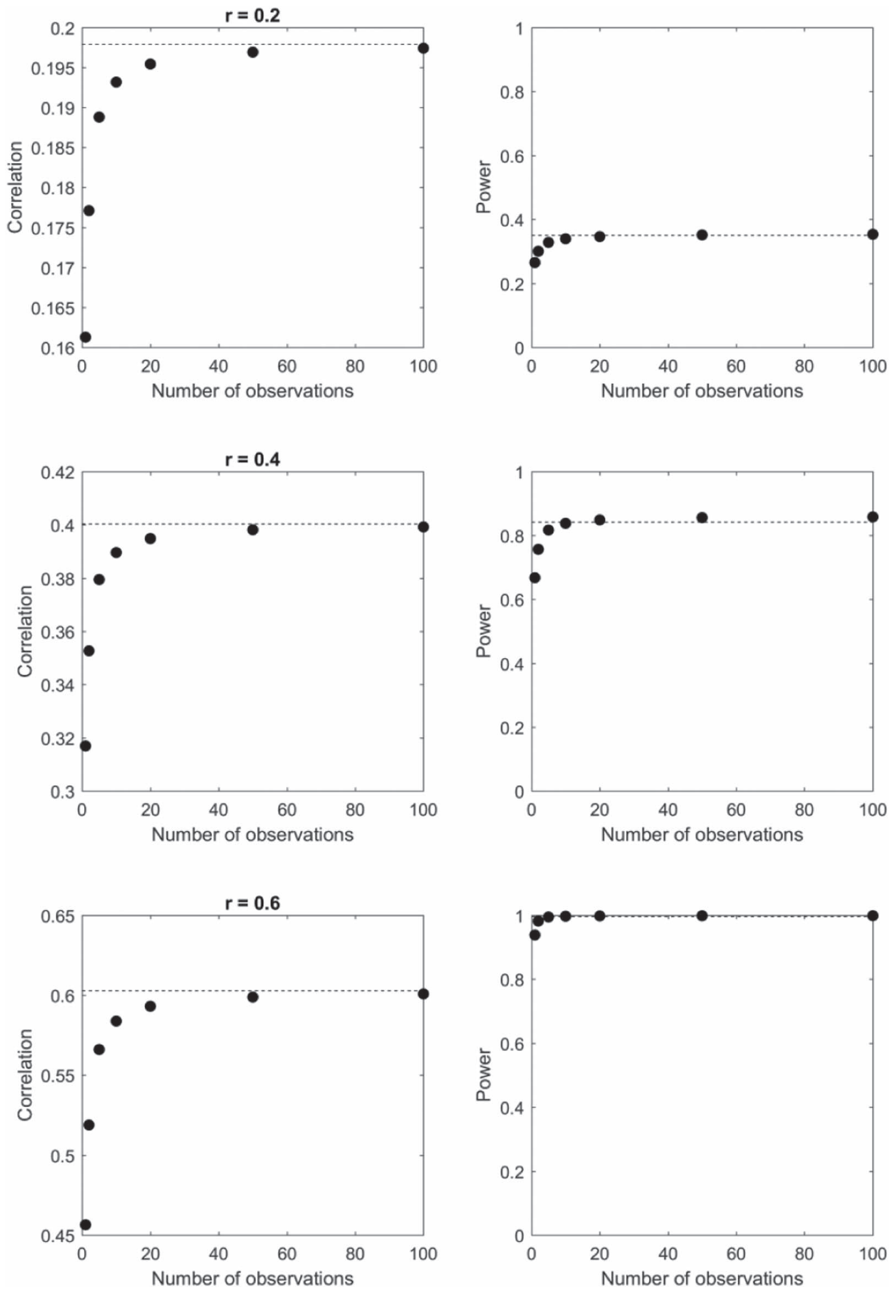


Note. See the online article for the color version of this figure.

(*Appendices continue*)

Figure A2

Recovery of Low, Medium, and High Correlations (Upper, Middle, and Bottom Panels) Between 41 Data Points, for Each of Which Different Numbers of Observations Are Available (Left Panels), and Statistical Power to Detect a Correlation as a Function of the Number of Observations (Right Panels)



Note. The horizontal lines in the left column indicate the correlation in the data-generating mechanism. The horizontal lines in the right column indicate the maximum power achievable with 41 pairs of data points.

recovered for different numbers of observations (i.e., sample sizes) on which each data point is based. This is informative for the robustness of our PCA results as the goal of PCA is to extract commonalities between variables based on correlations. The simulation also computed statistical power to detect a correlation for the different sample sizes.

The procedure in the computer simulations was as follows. Mimicking the data situation that eventually fed into our PCA,

(*Appendices continue*)

we generated 41 synthetic data points (representing the 41 food products in our study) on two data vectors (representing the food characteristics in our study) that were correlated. To obtain correlated vectors of data points, we created a vector with random numbers (in the range [0,1]), then replicated that vector and added random zero-centered noise to the second vector. The noise had a standard deviation σ that ensured either a low (average correlation of $r = .2$ across the iterations of the simulation), medium ($r = .4$), or high ($r = .6$) correlation between the vectors (specifically, this was the case for $\sigma = 1.4, .65$, and $.38$, respectively). We tested how well the correlations could be recovered when for estimating each of the data points in the vectors different numbers of observations were available (the values of each data point were then computed as the average across the values in each sample). We considered seven levels of sample size, $N = 1, 2, 5, 10, 20, 50$, and 100. The data in each sample were randomly drawn from a normal distribution with a mean that corresponded to the value of the data point for which the actual correlation was computed and a standard deviation of .2 (the level of variation was chosen to approximate the level of variability in our data for the adults group, quantified by the average normalized *SD* of the ratings on each characteristic; sensitivity analyses showed that our conclusions also hold when approximating the somewhat higher variability in the adolescent group). For a given level of correlation and each sample size we repeated the procedure 1,000 times, and also each implementation of a correlation level was repeated 1,000 times, leading to a total of 1,000,000 iterations for each level of sample size. For each iteration, we calculated the correlation between the 41 points, with each point being the average value across the observations in each sample, and determined a frequentist p value for the correlation. In addition, we determined the statistical power for detecting the correlation, with power calculated as the proportion of iterations across the 1,000,000 runs of the simulation in which the (positive) correlation was significant ($p < .05$, one-tailed).

The results are shown in Figure A2, with the upper, middle, and lower row referring to the conditions with low, medium, and high correlations, respectively. The panels on the left show how the average (across iterations) recovered correlation approximates the average true correlation (dotted horizontal line) with growing sample size; the panels on the right show how statistical power increases with sample size. As shown, the true correlations could be recovered relatively accurately already at sample sizes of $N = 10$. It was also at $N = 10$ that statistical power started plateauing at the maximum level of power achievable with 41 pairs of data points (indicated by the horizontal lines in the right column). Most importantly, for correlations of medium and large size—which are most relevant for the solutions extracted by a PCA and for interpreting the solutions—statistical power is around .8 or higher. Overall, these results suggest that even with the sample size of our smallest respondent group ($N = 36$ in our adolescent group), correlations (the basis for PCA) between 41 data points can be estimated relatively accurately for correlations of medium to large size. The MATLAB code for the simulation can be found at https://osf.io/n8h9j/?view_only=d291ccdbb0fa4e2b86ea6d993e93930b.

Appendix B

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 α 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 α 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.

(*Appendices continue*)

Table B1
Level of Agreement (Indexed by Krippendorff's α) 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
Local 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 α can produce negative values if coders consistently agree to disagree, follow different coding instructions, or have a conflicting understanding of them.

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 B1.

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 B2.

Table B2
Level of Agreement (Indexed by Krippendorff's α) 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 yogurt	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 yogurt	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
Sun-dried 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.

(*Appendices continue*)

Appendix C

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 C1 shows the results of the variance component estimation.

As shown in Table B1, 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 error. 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.

Table C1
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.

The third step involves balancing the fit and parsimony of a model 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 et al., 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 C2 and C3, 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 C2 and C3 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 1,000 bootstrap samples (Kiers, 2004).

(*Appendices continue*)

Table C2

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
Local 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 C3

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 yogurt	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 yogurt	−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

(*Appendices continue*)

Table C3 (*continued*)

Item	Protein-rich foods	95% CI		Fruits and vegetables	95% CI		Processed foods	95% CI		Fit (%)
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
Sun-dried 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.

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