How protein containing foods are represented in memory? A categorization study

Sylvie Chollet, Coraline Sénécal, Laura Woelki, Adeline Cortesi, Viridiana Fifi, Gaëlle Arvisenet, Dominique Valentin

How protein containing foods are represented in memory? A categorization study

S.Chollet

C.Sénécal

L.WoelkibA.Cortesi

V.Fifi

G.Arvisenet

D.Valentin

Highlights

Origin is more frequently used than process to categorize food pictures

Unprocessed plant foods and unprocessed meats are clearly two distinct categories

Participants are more likely to use the process dimension for highly processed food

The property most frequently attached to meat item is their animal origin

The health property is strongly associated to unprocessed plant food

Abstract

Protein intake for humans is a major issue as the production of meat is contributing to the excess of greenhouse gas emissions and loss of biodiversity. To cover the upcoming protein demand in a sustainable way, a shift from animal-based food items to plant-based ones will be necessary. The aim of this article is to better understand the representations people have of protein containing food and more specifically, the role of origin and process in these representations. Two categorization tasks of pictures of protein containing foods are used: a forced extraction task and an extended sorting task including a property generation step. Our results show that, globally, the origin dimension is preponderant, except for ready-to-eat dishes for which the process dimension is more important. While plant and animal unprocessed foods are clearly two distinct categories with specific properties, plant-based and animal-based ready-to-eat dishes share a large number of properties and thus could be a potential way of decreasing meat consumption by substituting one by the other.

Keywords

Categorization, representation, flexibility, protein containing food

1 Introduction

In Western cultures, animal products, in particular meat, play a major role in protein provision (Fiddes, 1991; Jallinoja et al., 2016); although, the negative effects of intensive livestock farming on the environment, especially on carbon dioxide (CO_2) emission and loss of biodiversity, are well established. The production of plant protein sources - such as legumes, seeds, nuts, and cereals - is linked to a smaller CO_2 emission than food products from animal origin (Carlsson-Kanyama & González, 2009; Godfray et al., 2010; Virtanen et al., 2011). To cover the upcoming protein demand in a sustainable way, a shift from animal-based food items to plant-based ones would thus be necessary. However, the way to implement this shift remains an unsolved problem, as meat still plays a central role in the representations of meal structure in most Western cultures (Melendrez-Ruiz, Chambaron, et al., 2019; Tziva et al., 2020).

Previous surveys suggest that the main barriers for plant-based food consumption are a lack of knowledge and a negative image of these food items (de Boer et al., 2017; de Boer & Aiking, 2019; de Gavelle et al., 2019; Graça et al., 2019; Melendrez-Ruiz, Buatois, et al., 2019; Vainio et al., 2016). Health information or emotional messages might not be powerful enough for consumers to go beyond these barriers. Despite an awareness of the situation and a behavioral intention to reduce meat consumption (Harguess et al., 2020) several studies highlighted the existence of an attitude-behavior gap whereby consumers' in-store behavior does not align with their attitude (Hoek, Luning, et al., 2011). To facilitate the transition toward plant-based food, we need to understand the representations that people have of protein containing food from plant and animal origin, as food representations guide food practices and *vice versa* (Urdapilleta et al., 2005). One way of exploring these representations is to look at the way individuals categorize food stimuli. In this paper, we will focus on the structure and properties of protein containing food categories. Our assumption is that food items that belong to nearby categories or to categories sharing properties will be more easily exchangeable than items considered as belonging to different, more distant categories (Hoek, van Boekel, et al., 2011). The rationale behind this assumption is that one of the main use of categories is to infer properties from the known items of a category to new items. So, if a new item is recognized as belonging to a certain food category, the properties of the category will be extended to this new item.

Research on food category structures and properties is rather scarce. In the 80's, Rozin & Fallon, (1980) were among the first to be interested in food categorization. They tried to understand how humans differentiate between edible and non-edible items. They designed a questionnaire to capture the essential characteristics of distaste, danger, and disgust food categories among American college students. Their results showed that items in the disgust category were in majority from animal origin: arthropods, mammals, other invertebrates, parts of edible animals (e.g., liver, kidney, tongue), and non-mammal vertebrates. Non animal items (plant and mineral origin) were much less frequent in the disgust category. They were rejected simply because they are not considered food in the American culture (e.g., grass or sand). Overall, it seems that there are some clear psychological distinctions among foods that share similar nutritional or sensory properties and these distinctions are linked to the origin of the foods.

Since this seminal work of Rozin and Fallon, to our knowledge, very few studies have investigated how adults categorize food items. Ross & Murphy (1999) examined the different types of categories people have about foods. They gave participants a list of basic food items and asked them to generate some categories for each of these foods. They obtained three main kinds of categories based on either taxonomic (common properties) or script (same role in an event) relation. About 50% of the responses corresponded to the type of foods (e.g., breads, dairy foods, fruits), about 40% to the situations in which the food could be eaten (e.g., breakfast foods, snack) and about 10% were linked to the food macronutrients (e.g., proteins, carbohydrates). Using a multiple card task, Blake et al. (2007) also observed three kinds of food categorization: personal-experience-based (food I like vs. food I dislike), context based (winter vs. summer food) and food-based. The latter included three subdimensions: Food group (fruit and vegetable vs. meat), nutrient composition (starch vs. protein), and physical characteristics (sweet vs. salty foods). These taxonomic or script-based food categories seem to be already acquired by the age of 2 to 3 years (Nguyen & Murphy, 2003). Children above 4 or 5 years-old are able to generalize the psychological and biological properties of food items within a type of food: If an apple is good for health, a pear is also good for health; as they both belong to the fruit category (Nguyen, 2007; Thibaut et al., 2020).

Although food categorization seems to be generally performed at the level of food items, it can also occur at other scales. For example, Aschemann-Witzel et al. (2019) examined how people categorize food ingredients using a projective mapping technique. The underlying dimensions that emerged were: 1) kind of ingredients, 2) specific function of ingredients (e.g., flavoring, feeling), 3) healthiness and 4) familiarity. Recent work in neuroscience highlighted other important dimensions of food categorization. Among those dimensions the most studied one is food energy density: the energy content of visually presented foods modulates brain activation during food/nonfood categorization (Killgore et al., 2003). Food transformation attracted also a lot of research. EEG studies suggest that natural foods (e.g., apples, tomatoes, carrots) are processed differently from transformed foods (e.g., pasta, cakes, pizza) just like natural objects are processed differently from artefacts (Coricelli et al., 2019; Warrington & Shallice, 1984). Experimental data indicate that the former are more frequently described with sensory or internal biological (e.g., sweet, bitter) properties whereas the latter are more frequently associated with functional (e.g., suitable for breakfast) properties (Rumiati & Foroni, 2016) which does make sense since artefacts are intentionally made to serve a given purpose, whereas natural objects exist without human intervention and intention (Lafraire et al., 2020). Along the same line, Pergola et al. (2017) report a strong association of natural food (e.g., apple) with sensory primes and a stronger association between transformed food (e.g., lasagna) and functional primes.

In this article we will focus on the origin (animal *vs*. plant) and processing degree (unprocessed *vs*. transformed food) dimensions. If the first dimension is mainly dichotomous -- in natural foods, proteins are of plant or animal origin -- the distinction between natural and processed food is not as clear cut, which was also noted for the distinction between natural objects and artefacts (Gelman, 1988). In the case of food, the processing dimension is probably better represented as a continuum going from totally natural (e.g., fresh fruit) to highly processed (fruit compote with preservative, added aroma, and texture agent). In contrast to natural food, processed foods have very fuzzy boundaries and do not possess an "inner essence" based on DNA to distinguish them from one another; like for example an apple is different from an orange.

The aim of this article was to better understand the role of origin and process in protein containing food representation. We carried out two experiments using categorization tasks of protein containing food pictures. The first experiment used a forced categorization paradigm and the second experiment a free categorization paradigm. Our first hypothesis (H1, experiment 1) was that the importance of origin would depend on the degree of processing of food. Because the boundaries between natural food are sharper than the boundaries between processed foods, we expected origin to be more salient in natural foods than in processed foods. Our second hypothesis (H2, experiment 1) was that the effect of origin would also depend on the structural similarity between the foods. Based on the observation that objects belonging to the same category tend to be more similar in shape than objects belonging to different categories (Gerlach et al., 2015), we expected the effect of origin to be less important for food structurally similar than for food structurally dissimilar. Our third hypothesis (H3, experiment 2) was that the origin and process dimensions were highly activable in memory and thus spontaneously used in a free categorization paradigm. Our fourth hypothesis (H4, experiment 2) was that, based on previous work on artefact and natural categories, unprocessed foods would be associated with sensory or inner biological properties and highly processed foods with functional properties.

2 Material

To explore protein containing food representations, we used 64 pictures of different foods including meat, legumes, and cereals. While this selection is not representative of all available protein containing foods, it constitutes a workable sample which has the advantage to be manageable and wide enough to test our hypothesis. These pictures were organized in six categories (Figure 1) with three levels of processing on the continuum from natural to highly processed foods (unprocessed, slightly processed, highly processed), and two different origins (animal vs. plant). We labeled these six categories as follows: 1) unprocessed meat (UA), 2) legumes and cereals (UV), 3) processed meat (PA1, steak and sausages), 4) processed legumes and cereals (PV1, patties and sausages), 5) ready-to-eat dishes with meat (PA2, pasta and couscous box) and 6) ready-to-eat dishes without meat (PV2, veggie pasta and couscous box). Each category was represented by either eight (processed categories) or sixteen (unprocessed) pictures to ensure the generalizability of results. Overall, the number of processed and unprocessed food pictures or animal-based and plant-based food pictures was balanced.

The pictures were chosen to cover a large range of protein containing food. Different types of meat were presented for the unprocessed meat group, (beef, chicken, …) with different cuts (slice, steak, filet, ...). For unprocessed plant foods, different types of legumes and cereals were presented (lentils, beans, quinoa…) in different packaging. For processed foods, we additionally manipulated the similarity between items from animal and plant origin (i.e., Similar: chopped beef steak vs. soy steak; pasta with meat vs. pasta without meat. Dissimilar: chopped beef steak vs. plant sausage; pasta with meat vs. couscous without meat). This was done to evaluate the impact of the structural similarity between animal- and plant-based processed foods in the categorization process. Pasta and couscous boxes were chosen as ready-to-eat dishes because they exist with and without meat. A series of pre-tests was carried out to make sure that the food pictures were easily identifiable either visually because the packaging was transparent or via the labels and images on the packaging. All the protein containing food pictures were presented to participants either on a computer screen (1366 pixels × 768 pixels, Experiment 1) or in the form of plastic cards (65 mm×65 mm; 307 pixels × 307 pixels, Experiment 2).

3 Experiment 1: Effect of origin and process dimensions in a forced extraction task

Experiment 1 was designed to evaluate the relative importance of origin and processing degree in food categorization (H1 & H2). A forced extraction task was used. Triplets of pictures combining protein containing food of different origin or processing degree were presented to the participants who had to indicate the odd one. The extraction task is classically used in the study of categorization processes to determine which critical dimensions are extracted as being defining of contrasting categories. The rationale behind this task is that categorization is grounded in the dimensions that distinguish categories: as a result of experience with stimuli belonging to different categories, the cognitive system discovers the dimensions that discriminate best between the categories for a given individual based on his/her representation system.

3.1 Material and method

3.1.1 Participants

In total 82 volunteers participated in the study; 26 males and 56 females aged from 18 to 28-year-old (mean age: 21.54 ± 2.16 years). All were students from the University of Burgundy.

3.1.2 Materials

The 64 protein containing food pictures presented in Section 2 (Figure 1) were used in this study to create two equal sets of 32 pictures (Set A and Set B). Both sets included unprocessed and processed food; however, they differed in terms of processed food items. Set A contained slightly processed food from Categories 3 (processed meat) and 4 (processed legumes and cereals) and Set B highly processed food from Categories 5 (ready-to-eat dishes with meat) and 6 (ready-to-eat dishes without meat). For both sets, the unprocessed food pictures came from Categories 1 (unprocessed meat) and 2 (legumes and cereals).

The triplets within each set were obtained by crossing the origin and process dimensions so that each triplet consisted of at least one animal-based (A) and one plant-based (V) as well as at least one processed (P) and one unprocessed (U) protein containing food picture. Crossing all possible picture categories (PA, PV, UA, UV) led to four triplet conditions: Cond. 1: PA-PV-UA; Cond. 2: PA PV–UV; Cond. 3: UA-UV–PA and Cond. 4: UA-UV-PV. In Condition 1 and 2, half of the triplets contained similar PA-PV pictures (e.g. chopped beef steak vs. soy steak) while the other half contained dissimilar PA-PV pictures (e.g., chopped beef steak vs. plant sausage).

3.1.3 Procedure

Firstly, participants completed a consent form in which the task was explained, and an information sheet to obtain general information (sex, age, level, field of study). The participants received the following instructions: “You will see three food pictures on the screen at the same time and you will have to decide which one, according to your opinion, is the odd one. There is no right or wrong answer, we are interested in your personal opinion. As we will measure the time you need to make your decision, click on the button below the picture as soon as you have made your choice. You don't have to give any justification, so answer intuitively and without reflection."

The three pictures in a triplet were simultaneously presented in the center of a computer screen. Half of the participants saw the triplets from Set A first, while the other half saw the triplets from Set B first. Each participant had to evaluate successively the 32 triplets of each set with a 30 second break between the sets. The food pictures were presented to the participants, via E-Prime (Version: 3.0.3.80, Studio Version: 3.0.3.82, Psychology Software Tools, Sharpsburg, PA, USA).

3.1.4 Data analysis

Two dependent variables were used to test our hypotheses: Frequency of occurrence of the underlying dimensions (origin and process) and reaction time (RT). As the results obtained for the two variables converged, for simplicity sake, we present only the results for the frequency of occurrence. The RT results are presented in additional material (1).

Data were first coded by determining the dimension participants used to select the odd item in each triplet as shown Table 1. For example, in Condition 1 (PA-PV-UA), if PV was chosen to be the odd one, the underlying categorization dimension would be 'origin' as the other pictures (PA and UA) represent a protein containing food from animal origin. If UA was chosen by the participant the underlying dimension was 'process', since it is the only unprocessed food item in this triplet. The term 'other' was used to code cases in which PA was chosen neither on the basis of the origin nor process dimension.

Table 1. Coding scheme for each condition and triplet.

	Conditions	**Underlying dimensions**
Condition 1	**PA** PV UA	Other
	PA **PV** UA	Origin
	PA PV **UA**	Process
Condition 2	**PA** PV UV	Origin
	PA **PV** UV	Other
	PA PV **UV**	Process
Condition 3	**UA** UV PA	Other
	UA **UV** PA	Origin
	UA UV **PA**	Process
Condition 4	**UA** UV PV	Origin

UA **<u>UV</u>** PV	Other
UA UV **<u>PV</u>**	Process

The triplets in Conditions 1 and 2 were additionally coded to reflect the structural similarity between the two processed protein containing foods (PA and PV). The triplets containing similar PA-PV pictures (e.g. chopped beef steak vs. soy steak) were coded with the word "similar" and the triplets containing dissimilar PA-PV pictures (e.g. chopped beef steak vs. plant sausage) were coded with the word "dissimilar".

Chi^2 tests were carried out at three levels ranging from the most general to the most specific to evaluate: 1) the effect of type of set, 2) the effect of triplet condition, and 3) the effect of structural similarity.

3.2 Results

A total of 5248 responses was collected. A chi-square test indicated that the dimensions "origin", "process" and "other" were not used equally ($X^2 = 21.19$; $p < 0.001$). Overall, the dimension "origin" was the most frequently used (57.1%), followed by the dimension "process" (32.9%). The dimension "other" was used only in 10.0% of the cases.

3.2.1 Interaction between dimensions and degree of processing (H1)

To check whether the dimension used by the participants to perform the task depends on the degree of processing, we compared the results obtained for Set A including slightly processed food with those obtained for Set B including highly processed food. We expected the frequency of origin to be higher for Set A than for Set B. Figure 2 represents the frequency of occurrence of the origin, process, and other dimensions as a function of the set of protein containing food pictures. For each set, a total of 2624 responses was collected. A Chi^2 test shows a significant difference between the two sets, with participants being more likely to categorize food pictures according to origin when presented with Set A and according to process when presented with Set B ($X^2 = 934.76$, $p < 0.001$). No difference was observed for the other dimension.

To verify if the interaction between dimension and degree of processing is modulated by the composition of the triplets (cf Table 1), we analyzed the data separately for each condition within each set. Figure 3 shows the frequency of occurrence of the origin, process, and other dimensions in each condition for the two sets of protein containing food pictures. For Set A, the triplet condition influenced globally the response of participants ($X^2 = 930.66$, $p < 0.001$). Origin was significantly more frequent than process, whatever the condition ($p < 0.001$). This superiority of origin over process was significantly higher in Condition 1 and 3 (two animal items) than in Condition 2 and 4 (two plant items). In Condition 4 (unprocessed animal vs. processed and unprocessed plant items), the other dimension was significantly higher than in all other conditions of Set A. For Set B, the choice of participants also changed according to the condition ($X^2 = 693.63$, $p < 0.001$). Origin was always significantly more frequent than process when the triplet included two unprocessed pictures (Condition 3 and 4). Inversely, process was significantly more frequent than origin when the triplets included two processed items (Condition 1 and 2).

3.2.2 Effect of similarity (H2)

Figure 4 shows the frequency of occurrence of the origin, process, and other dimensions for similar and dissimilar pictures in each condition and each set of food items. Globally, the main effect of set remained significant: The origin dimension was more frequent for Set A ($p < 0.001$), whereas for Set B, it was the process dimension ($p < 0.001$). Additionally, a significant effect of similarity was observed in Condition 1 for Set A ($X^2 = 48.93$, $p < 0.001$) and in condition 1 and 2 for Set B ($X^2 = 8.02$, $p < 0.05$ and $X^2 = 18.17$, $p < 0.001$): the frequency of occurrence of process was higher for similar pictures and the frequency of origin for dissimilar pictures.

3.3 Discussion

This experiment suggests that the level of processing of food items has an influence on their categorization. This influence is modulated by the composition of the triplets. However, no effect of structural similarity between pictures was observed.

When the triplet included two **unprocessed food items**, only a few participants used the process dimension. Origin in this case was very salient, which suggests that unprocessed plant-based food and unprocessed meat are clearly two distinct food categories. To validate this interpretation, we asked an additional group of participants to rate the perceived similarity between all possible pairs of unprocessed plant-based foods and unprocessed meats in our set on a seven-point scale, going from 1 not at all similar to 7 very similar (Additional material 2). As expected, the average similarity score was very low (mean=1,39; SD=0,86). Such taxonomic food categories have been previously reported in the literature (Ross & Murphy, 1999) and seem to be well anchored in food classification system. Furthermore, they seem to be independent of context (Blake et al., 2007). Additionally, the unprocessed foods used in this study were close to natural types of categories (e.g., animal vs. plant) which are known to have sharp and objective boundaries compared to artefacts which tend to have more flexible boundaries (Lafraire et al., 2020).

Likewise, participants were more likely to categorize **slightly processed food** items according to origin, rather than to process. This effect was somewhat modulated by the composition of the triplets: The predominance of the origin dimension was somewhat reduced when the triplets included two plant items as opposed to two meat items. This result suggests that participants perceived a higher similarity between unprocessed and slightly processed items from animal origin than between legumes or cereals and slightly processed plant-based food. Accordingly, the perceived similarity between unprocessed and slightly processed meats (mean=4,75; SD=1,74) was significantly higher than that between unprocessed and slightly processed plant-based food (mean=2,60; SD=1,63). In agreement with this interpretation, participants took less time to indicate origin as response for the triplets including two meat items than for the triplets including two plant items. The origin dimension is thus more salient for the animal food items used in our study than for plant-based ones. This can be due to the appearance of the slightly processed plant foods which were evaluated as more similar to slightly processed animal foods (mean=2,98; SD=1,65) than to unprocessed plant foods. Thus, it seems that perceptual based information such as the form or the color of a food might play an important role in adult food categorization as was already reported by Hoek, Luning, et al. (2011) for meat and meat substitute items. Previous work suggested that the mode of presentation of food affects also children food behavior by helping them identifying the food items. For example, children judged a sliced fruit more edible that an unprocessed one (Lafraire et al., 2020). It might also be due to the fact that slightly processed meat items share more inner properties with the unprocessed item from which they originate than do slightly processed plant items.

In regard to the **highly processed food,** participants were more likely to use the process dimension than the origin dimension, independently of the number of animal or plant-based items in the triplet. In agreement with this observation, participants answered faster when they used the process dimension for highly processed food than the origin dimension (see additional material 1). This suggests that the process dimension is more salient in highly processed food than in slightly processed food. This difference in saliency may be due to a difference in similarity as the perceived similarity between highly processed items (mean=4,39; SD=1,95) was significantly higher than that between slightly processed items (mean=3,39; SD=1,66). Both the high similarity between highly processed items and the saliency of the process dimension might be linked to perceived energy density, as previous work showed that the energy density of food is one of the main underlying factors in the differentiation of raw and processed food items. (Foroni et al., 2016; Foroni & Rumiati, 2017; Greenwald et al., 1998). Participants in our experiment may have considered that pasta and couscous meal boxes have a higher energy density than unprocessed or slightly processed food. Another plausible explanation is that participants relied on other properties conferred by the process, such as distance from edibility (i.e., work still required to bring the food item into an edible state; Foroni et al., 2013). Couscous and pasta boxes are complete dishes, while unprocessed or slightly processed foods should be combined with another food item to constitute a dish. Hence, the saliency of the process dimension when two ready-to-eat items were in a triplet might be driven by inference on the function attributed to highly processed food or actions they require in order to be prepared. Previous work showed that adults tend to make inferences about function when confronted with processed food whereas for unprocessed foods they tend to infer biological properties (Pergola et al., 2017). Lafraire et al. (2020) talk about "functional affordance" in resonance with Gibson, (1966) perceptual affordance, as a possible mechanism behind this effect: Highly process food items are readily perceived as being easily eatable, independently of their animal or plant origin.

4 Experiment 2. Free sorting task and property generation

The objective of Experiment 2 was to determine whether the origin and process dimensions were used spontaneously by adults when asked to categorize food items (H3) and to explore the properties attached to unprocessed, slightly and highly processed foods. Based on the results of Experiment 1, we expected a decrease of the weight of the origin dimension in the categorization process and an increase of the number of shared properties as a function of the degree of processing of the foods. More precisely, we expected unprocessed animal and plant-based food items to form very distinct categories with only a few shared properties and highly processed foods to form a single category with many shared properties regardless of their origin. We also expected unprocessed food items to be associated with sensory or inner biological properties and highly processed foods with functional properties (H4).

4.1 Material and method

4.1.1 Participants

Forty participants were recruited from the Campus of the University of Burgundy, including 22 women and 18 men. They were aged from 20 to 27 years (mean age: 20.33 ± 1.72 years) and were mostly students from different fields (biology, human science, geoscience and agriculture).

4.1.2 Materials

All 64 protein containing food pictures presented in Figure 1 were used in this experiment. In order to check the generalization of our results the 64 pictures were separated in two sets (Set 1 and Set 2) and the same task carried out with each set. Half of the pictures of each category were randomly attributed to Set 1 and the other half to Set 2 under the constraint that 1) for PA1 and

PV1: two steaks and two sausages pictures and 2) for PA2 and PV2: two couscous and two pasta pictures were selected for Set 1 and Set 2. The pictures were presented to the participants in the form of plastic-coated color cards (65 mm×65 mm) identified by a random 3-digit code on the verso.

4.1.3 Procedure

The experiment was conducted individually. First, participants completed an informed consent form and a demographic form (sex, age, field of study). The sets of cards were shuffled between each participant to ensure randomness before being presented simultaneously to the participant on a white table. Then, the sorting instructions were given to participants, indicating that they could use any criteria they wanted to sort the pictures, with the exception that they should not make hedonic categories (according to their personal preferences: "I like" vs. "I do not like"). We deliberately chose to focus on non-hedonic dimensions because we were interested in accessing stable collective representations stored in semantic memory rather than *ad hoc* individual representations. There was no time limit. They were free to make as many groups as they wanted and to include as many pictures in the groups as they wanted. After participants had formed their groups, they were asked to indicate the properties that would make it possible to define these groups. They were also told that there was no time limit for answering these questions. Participants could give as many properties for each group as they wished, and no restrictive instruction was given. Half of the participants did the sorting task with Set 1 and the other half with Set 2.

4.1.4 Data analysis

Sorting data

Sorting data obtained for the two sets of protein containing food pictures were analyzed separately. For each set, data were encoded in a rectangular matrix where the rows represented the pictures and the columns the participants. The groups of pictures formed by each participant were indicated in these matrices by arbitrary numbers: "1" for all pictures placed in the first group, "2" for all pictures placed in the second group and so on. The matrices were analyzed with Distatis (Abdi et al., 2007). DISTATIS is a generalization of multidimensional scaling (MDS) that takes into account individual data, by performing the calculation directly on individual distance matrices. It starts by transforming the individual sorting data into cross-product matrices as in classical MDS and evaluating the similarity between these matrices using RV coefficients. Then, it computes a compromise matrix which is the best aggregate of the individual cross-product matrices and analyses it with a Principal Component Analysis giving rise to a similarity map of the stimuli (here the Distatis positioning map). Two stimuli close together on this map were often sorted together. As in classical MDS the meaning of the map dimensions is inferred from the characteristics of the stimuli the most correlated with these dimensions.

A bootstrap resampling technic with replacement was used to build confidence ellipses around the protein containing food pictures. Then, a hierarchical cluster analysis (HAC) using the Ward criteria and Euclidean distances was applied to the picture coordinates in the Distatis spaces. The clusters obtained for the two sets of pictures were compared to assess the stability of the data. All statistical analyses were performed using R (Version 3.5.2) for Windows with the DistatisR package (Beaton, Chin Fatt, Abdi, version 1.0.1).

Properties

The terms generated for the two sets of protein containing food pictures were merged. They were lemmatized and then grouped according to their meaning. During this process, only terms corresponding to properties were kept (e.g., denominations of food items such as chicken legs were deleted). This preprocessing was carried out independently by two researchers. Once the two researchers agreed on the groupings, the frequencies of occurrence of the properties were calculated for the six protein containing food picture categories (unprocessed meat, legumes and cereals, processed meat, processed legumes and cereals, ready-to-eat dishes with meat, ready-to-eat dishes without meat). Properties used by only one of participant were not taken into account in the analyses.

Two analyzes were performed on the frequencies of occurrence of the properties. Firstly, for each of the six categories, a word cloud has been created. The properties best defining the categories were identified using a hypergeometrical law to compute their probability of characterizing a category with an alpha level of 5% (Lebart, Morineau, Piron, 1995). Second, a correspondence analysis (CA) was performed to visualize the distances between the six categories. Data processing and statistical analyses were performed with the statistical software SPAD®, V8.2 (Coheris, France)

4.2 Results

4.2.1 Accessibility of the origin and process dimensions in a free categorization task (H3)

Figure 5 and 6 show the projections of Set 1 and Set 2 food pictures onto the first three Distatis dimensions. For both sets, the first three dimensions of Distatis explained more than 75% of the variance (85% for Set 1 and 76% for Set 2). For both sets, the first dimension (69% and 65% of variance) opposed the meat items (UA and PA1) to the legumes and cereals (UV) and ready-to-eat dishes (PV2 and PA2). The second dimension (11% and 7% of variance) opposed the legumes and cereals (UV) to the ready-to-eat dishes with and without meat (PV2 and PA2). The small size of the confidence ellipses indicated a good reliability of the data reflecting a high consensus among participants for both sets. The third dimension (5% and 4 % of variance) opposed processed legumes and cereals (PV1) to other items. The HCA carried out on the projections of the food pictures onto the first three Distatis dimensions revealed a segmentation in four clusters for both sets. These clusters are identified on the Distatis maps (Figure 5 and 6). Cluster 1 included all meat items regardless of process. For both sets, this cluster projected on the negative side of the first Distatis dimension. Although the confidence intervals of the items of this cluster were small and overlapping, we can note that processed meats (PA1) were slightly different from unprocessed meats (UA). Cluster 2 consisted of legumes and cereals. Again, the confidence ellipses were rather small and overlapping within the cluster. Cluster 3 included all the ready-to-eat dishes: pasta, couscous, with and without meat. The confidence ellipses for ready-to-eat dishes with (PA2) and without meat (PV2) intersected with a small overlapping, which suggests that the presence or absence of animal protein was not a discriminating dimension for these food items. Both cluster 2 and 3 projected on the positive side of the first dimension in opposition to cluster 1. However, they were separated on the second dimension. Cluster 4 consisted of processed legumes and cereals. It was opposed to the three other clusters on the third dimension indicating that the food items included in cluster 4 were often set apart. An analysis of the raw data confirmed this observation as 13 and 12 out of the 20 participants (Set 1 and Set 2) formed a separate group with these processed legumes and cereals (PV1).

4.2.2 Effect of the type of categories on their associated properties (H4)

Fifty-nine properties emerged after preprocessing. As was already reported by Gaillard & Urdapilleta (2011) for the same type of task, these 59 properties included biological (e.g., animal or plant origin), nutritional contents (e.g., protein, starch, fiber, fat), functional (e.g., processed vs. unprocessed, need cooking, need to be reheated, meat substitute), evaluative (e.g., not-environment friendly, barbaric, no additive, healthy, time consuming, expensive), sensory (e.g., taste, texture). The type of properties depended on the type of foods. Some properties were preferentially associated with some food categories. For example, biological categories were more frequently used for unprocessed foods than for ready-to-eat dishes which were more frequently associated with functional and evaluative properties.

To have a closer look at the properties associated with the six food categories, we created a word cloud for each category. Figure 7 presents the six property clouds for each of the categories. These clouds show that the unprocessed and slightly processed meat categories (UA and PA1) were characterized by the same properties such as *meat*, *protein*, *animal origin*, *animal*, *animal protein*, *not environment friendly*. For slightly processed meat (PA1), the property *processed* was additionally displayed. By contrast, the unprocessed and slightly processed plant categories (UV and PV1) were associated with very different properties. While the category "legumes and cereals" (UV) was characterized with properties such as *healthy, vegetal, fiber, unprocessed, starchy food, need cooking, protein, no meat*, the category "processed legumes and cereals" (PV1) was mainly represented by *meat substitute* and in second position by *for vegetarian*, *no meat* and *vegetal*. Finally, the two ready-to-eat categories (PA2 and PV2) were characterized by the same properties whatever their origin (plant or animal). Their associated properties were *fast, ready to eat dish, bad for health, additive, unreliable, practical, need to be reheated, "malbouffe" (junk food)*.

A CA was performed on the food categories by properties table to visualize the distances between the categories. Figure 8 presents the first two dimensions of the CA map (79,12% of the variance). The first dimension (40.82 %) opposed unprocessed food categories (UA and UV) to highly processed one (PA2 and PV2). The second dimension (38.30 %) opposed the meat-based categories to the plant-based categories. Globally, when these two dimensions were crossed, three groups emerged. The first group was composed by highly processed items (PA2 and PV2) which were very close to each other and did not share any properties with the other groups: The properties that differentiated them from the other groups were either positive (*easy, practical, fast, ready to eat dish) or* negative (*bad for health, less healthy, malbouffe, additive, fatty acid, unreliable, less quality, tasteless).* At the opposite side, UV et PV1categories, which were described by different properties on the word cloud, presented here on the CA map, common characteristics around healthy and vegetal properties. These common properties opposed these two categories to UA and PV2 categories which were described by properties related to non-ethics and taste. What is the more noticeable is that plant and animal-based categories (UA-PA1 and UV-PV1) shared common properties such as nutritional (*protein, less fat, no additive*, *balanced*) and practical (*need cooking, not complete dish, unprocessed*) that let us think that these categories could be somewhat flexible.

4.2.3 Discussion

The first objective of Experiment 2 was to determine whether the origin and process dimensions are used spontaneously by adults when asked to categorize food items. The second objective of this experiment was to explore the properties attached to unprocessed, slightly, and highly processed food items from animal and plant origin. We expected unprocessed animal and plant food items to form very distinct categories with only a few shared properties and highly processed foods to form a single category with many shared properties regardless of their animal vs. plant origin. The results of the sorting task showed that participants based their sorting on these two dimensions but the role and preponderance of each of these dimensions depends on the type of food items.

For meat items, the process dimension does not seem to play an important role: slightly processed meat items (chop steaks and sausages) were frequently grouped with unprocessed meat items such as beef steaks or chicken filets and shared many properties. Both were clearly identified based on their animal origin (*meat* or *animal origin*) and shared biological (*protein*), functional (*need-cooking*), moral (*not-environment friendly, animal abuse, or barbaric*), and evaluative (*quality*, *health*) properties. Among all properties associated with these items, the most frequent one was animal origin as if this property transcended all other properties. The existence of a clear meat category separated from plant-based foods was also reported in other studies (Blake et al., 2007; Hoek, van Boekel, et al., 2011; Ross & Murphy, 1999). Only a few participants mentioned the process dimension (*processed* vs. *unprocessed*). The saliency of the animal-meat connection has been thoroughly discussed in the literature (see Benningstad & Kunst, 2020 for a recent review) in connection with what is called the "meat paradox" (Loughnan et al., 2010). Although they enjoy eating meat, meat eaters tend to dislike the idea of killing animals. To avoid the state of cognitive dissonance (i.e., discrepancy between what people think and what they do, Festinger, 1962) created by this paradox, people tend to dissociate meat items from their animal origin; especially people with meat-intensive diets. Yet, in the present results, as in Hoek, van Boekel, et al. (2011) the meat or animal origin was central for the categorization of protein containing food pictures yielding either positive evaluative properties linked to nutritional values or health or negative ones linked to animal welfare. This suggests the existence of an awareness of the animal origin of unprocessed or slightly processed meats among our participants. This awareness could be due to the fact that the present experiment was performed in France where cuisine plays a major role and people tend to be more aware of their food than in other industrial countries where food is less associated with pleasure. Some authors report that much of the time individuals are able to cope with contradictions arising from their eating behavior inhibiting thoughts creating the state of cognitive dissonance (Rothgerber, 2020). Meat eaters would, thus, inhibit thoughts linked to animal welfare and enhance thoughts linked to meat positive evaluations (e.g., *healthy*, *protein*, *quality, taste*). On the contrary, vegetarians promote the belief system that killing animals for food is unethical associating meat products with properties such as *animal abuse* or *barbaric*.

For plant items, the process dimension is more salient than for meat-based items. Although, raw and slightly processed plant-based items share numerous properties (healthy, no-meat, plant origin, for vegetarian, environment friendly) attesting that participants were aware of a common origin these items were rarely grouped together in the sorting task. Contrary to unprocessed meat items, unprocessed plant items were not associated with their origin in the first instance but with an evaluative property: *healthy.* The plant origin comes later, along with other biological properties linked to nutritional content: *protein, fiber, starchy food*. The saliency of the "healthy/unhealthy" dimension was previously reported in Furst et al. (2000) study on food classification. Using deep interview these authors highlight the link between this dimension and nutrients such as "fatty foods", "things with cholesterol, "sweets/sugared/sweetened things", "starches", and "low salt/full of salt". Interestingly, our results show that the notion of health was strongly associated with plant food items. This might be attributed to the recent government dietary recommendations. Indeed, these recommendations have been the subject of numerous communications (e.g. Iriti & Varoni, 2017; Rebello et al., 2014; Rio, 2017).

Slightly processed plant-based items were classified as a category in itself and were clearly identified based on their function: *meat-substitute.* Contrary to a previous study by Hoek, Luning, et al. (2011), our participants did not regroup slightly processed meat and plant items despite the visual similarities between them. In our study, slightly processed plant-based items shared more properties with unprocessed plant items than with slightly processed meat. Our participants associated meat substitutes clearly with veganism (*for vegetarians).* The separation between meat and meat-like food is anchored in consumers early taxonomic learning that meat constitute a basic food category distinct from plants. According to Hoek, van Boekel, et al. (2011) "*the fact that consumers roughly divide foods into animal and plant-based foods, and learn repetitively from early age on about meat as a basic food category, make it a difficult starting point for new meat substitutes to be regarded as an alternative for meat on the plate* (p. 378)". In agreement with this statement, a recent study on the acceptance of meat substitutes (Lemken et al., 2019) showed that a cluster of consumers consider buying processed legume products only if these products are not marketed as an alternative to meat. Another cluster preferred to directly substitute meat with specific legumes rather than having highly processed products. Such a strong negative attitude towards meat substitutes might explain why perceptual similarity was not enough, in our study, for consumers to group processed meat and meat substitutes; as it was done by participants in the Hoek et al (2011) study. In the latter, food items were presented unpackaged, thus, minimizing top-down effects. Our choice of presenting packaged food items is closer to the conditions in which food purchase decisions are made and so, our results may predict better how protein containing food are categorized in real life situation. Although the main function of processed plant-based item was identified as *meat-substitute,* these items were not grouped with meat items. In line with this observation, a recent study (Elzerman et al., 2021) showed that globally meat products were perceived as more appropriate than their vegetarian equivalents in many situations. However, a vegetarian hamburger was judged as more appropriated than the normal hamburger for the situation "when I want to eat a healthy meal". The evaluation of appropriateness was nevertheless affected by frequency of consumption of meat substitute with higher appropriateness ratings for the more frequent meat-substitute users. Further work on categorization of meat substitute should take this variable into consideration.

For ready-to-eat dishes the process dimension clearly overshadows the origin dimension. All ready-to-eat items have been grouped together even after having been isolated from unprocessed items to limit anchoring effects. In agreement, a recent dietary survey with 74470 participants (Julia et al., 2018) showed that ultra-processed foods are associated with unbalanced nutritional intake. Our study also highlights that ready-to-eat dishes are clearly associated to negative health properties, but they are also highly associated to functional properties such as practicality. Our results are in the line with those of Aviles et al. (2020) which showed that convenience, liking, and health and price considerations were the most relevant aspects determining the consumption of ready-to-eat animal-based meals for Spanish and Argentine consumers. It might be possible that ready-to eat dishes, whatever their origin, and their associated functional properties are so anchored that they erase the origin dimension. For plant and animal ready-to-eat dishes, functional properties take the upper hand.

To sum up, Experiment 2 showed that food items used in this study are categorized in four stable categories relatively distinct. Some of the properties attached to these categories are shared by several categories and others are specific to a given category. For example, the ready-to-eat category is isolated from other categories in that it does not share properties with other categories. On the contrary, the plant and animal categories share some biological (e.g., *protein, balanced, essential*) or functional properties (e.g., *need cooking, unprocessed, not complete dish*), creating some flexibility among those categories. Unexpectedly, despite visual similarities the slightly processed meat and slightly processed plant items constitute very different categories without shared properties.

In our study, we used two types of categorization tasks, a forced and a free task. These two tasks are complementary and were used as a way of testing the internal validity of our results. The fact that the same dimensions (origin and process) emerged from these two tasks highlights the importance of these dimensions in the categorization process of protein containing food. One limitation of our study is that in the free sorting task we asked participants to avoid using hedonic criteria. This choice was driven by the fact that we were interested in accessing stable collective representations stored in semantic memory and not *ad hoc* individual representations. However, it is possible that this instruction led to less spontaneous responses since participants might have made a cognitive effort to avoid using hedonic criteria. Another limitation is linked to the fact that the food items we selected in this study are not representative of all protein containing food and further work would be needed to validate the generalization of our results to a wider set of food items including fish, egg… Additional dimensions beside origin and process might emerged from such a wider set.

5 Conclusion

Our assumption was that items from categories sharing properties might be more interchangeable. In our results we saw that plant-based and animal-based ready-to-eat dishes share a large number of properties and thus could be a potential way of decreasing meat consumption by substituting one by the other. Properties attached to this category of food are mainly evaluative properties with both positive and negative valence. Due in part to their positive functional properties (*practical, easy, fast,…*) the consumption of ready-to-eat dishes including plant-based variants increased these last years. For example, a recent study by France Agrimer shows an 18% increase in the quantity of ready-to-eat dishes purchased by French households between 2008 and 2017 (France Agrimer, 2019). A solution to mitigate the negative image of this type of food could be to improve their nutritional properties. Launching such improved ready-to eat dishes on the market, along with nudging or labeling strategies, might gradually lead consumers to decrease their animal-based food consumption through perceptual learning. Eventually, this learning could generalize to other types of food. A remaining question is: Would it be possible to increase the flexibility of protein containing food category structure? A recent study, based on nudge theory, encouraged meat substitutes sales by placing them in pair with sensory similar meat products rather than in a separate vegetarian section (Vandenbroele et al., 2019). Such an approach could lead to an increase of the number of shared properties between meat products and their vegetarian counterparts. However, further work is needed to validate this approach and evaluate whether it has a long-term effect on category flexibility.

6 References

Abdi, H., Valentin, D., Chollet, S., & Chrea, C. (2007). Analyzing assessors and products in sorting tasks : DISTATIS, theory and applications. *Food Quality and Preference*, *18*(4), 627-640.

Aschemann-Witzel, J., Varela, P., & Peschel, A. O. (2019). Consumers' categorization of food ingredients : Do consumers perceive them as 'clean label' producers expect? An exploration with projective mapping. *Food Quality and Preference*, *71*, 117-128. https://doi.org/10.1016/j.foodqual.2018.06.003

Aviles, M. V., Naef, E. F., Abalos, R. A., Lound, L. H., Olivera, D. F., & García-Segovia, P. (2020). Effect of familiarity of ready-to-eat animal-based meals on consumers' perception and consumption motivation. *International Journal of Gastronomy and Food Science*, *21*, 100225. https://doi.org/10.1016/j.ijgfs.2020.100225

Benningstad, N. C. G., & Kunst, J. R. (2020). Dissociating meat from its animal origins : A systematic literature review. *Appetite*, *147*, 104554. https://doi.org/10.1016/j.appet.2019.104554

Bentall, R. P., Jones, R. M., & Dickins, D. W. (1999). Errors and Response Latencies as a Function of Nodal Distance in 5-Member Equivalence Classes. *The Psychological Record*, *49*(1), 93-115. https://doi.org/10.1007/BF03395309

Blake, C. E., Bisogni, C. A., Sobal, J., Devine, C. M., & Jastran, M. (2007). Classifying foods in contexts : How adults categorize foods for different eating settings. *Appetite*, *49*(2), 500-510. https://doi.org/10.1016/j.appet.2007.03.009

Carlsson-Kanyama, A., & González, A. D. (2009). Potential contributions of food consumption patterns to climate change. *The American Journal of Clinical Nutrition*, *89*(5), 1704S-1709S. https://doi.org/10.3945/ajcn.2009.26736AA

Coricelli, C., Foroni, F., Osimo, S. A., & Rumiati, R. I. (2019). Implicit and explicit evaluations of foods : The natural and transformed dimension. *Food Quality and Preference*, *73*, 143-153. https://doi.org/10.1016/j.foodqual.2018.11.014

de Boer, J., & Aiking, H. (2019). Strategies towards healthy and sustainable protein consumption : A transition framework at the levels of diets, dishes, and dish ingredients. *Food Quality and Preference*, *73*, 171-181. https://doi.org/10.1016/j.foodqual.2018.11.012

de Boer, J., Schösler, H., & Aiking, H. (2017). Towards a reduced meat diet : Mindset and motivation of young vegetarians, low, medium and high meat-eaters. *Appetite*, *113*, 387-397. https://doi.org/10.1016/j.appet.2017.03.007

de Gavelle, E., Davidenko, O., Fouillet, H., Delarue, J., Darcel, N., Huneau, J.-F., & Mariotti, F. (2019). Self-declared attitudes and beliefs regarding protein sources are a good prediction of the degree of transition to a low-meat diet in France. *Appetite*, *142*, 104345. https://doi.org/10.1016/j.appet.2019.104345

Elzerman, J. E., Keulemans, L., Sap, R., & Luning, P. A. (2021). Situational appropriateness of meat products, meat substitutes and meat alternatives as perceived by Dutch consumers. *Food Quality and Preference*, *88*, 104108. https://doi.org/10.1016/j.foodqual.2020.104108

Festinger, L. (1962). Cognitive Dissonance. *Scientific American*, *207*(4), 93-106.

Fiddes, N. (1991). *Meat, a Natural Symbol*. Routledge.

Foroni, F., Pergola, G., Argiris, G., & Rumiati, R. I. (2013). The FoodCast research image database (FRIDa). *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00051

Foroni, F., & Rumiati, R. I. (2017). Food Perception and Categorization : From Food/No-Food to Different Types of Food. In H. Cohen & C. Lefebvre (Éds.), *Handbook of Categorization in Cognitive Science (Second Edition)* (p. 271-287). Elsevier. https://doi.org/10.1016/B978-0-08-101107-2.00012-9

Foroni, F., Rumiati, R. I., Coricelli, C., & Ambron, E. (2016). A bait we cannot avoid : Food-induced motor distractibility. *Brain and Cognition*, *110*, 74-84. https://doi.org/10.1016/j.bandc.2015.12.003

Furst, T., Connors, M., Sobal, J., Bisogni, C., & Falk, L. W. (2000). Food classifications : Levels and categories. *Ecology of Food and Nutrition*, *39*(5), 331-355. https://doi.org/10.1080/03670244.2000.9991623

Gaillard, A., & Urdapilleta, I. (2011). Sorting Food Labels and Describing Properties of Categories : Stability of Results between and within Subjects. *Psychological Reports*, *109*(1), 187-207. https://doi.org/10.2466/10.13.22.28.PR0.109.4.187-207

Gelman, S. A. (1988). The development of induction within natural kind and artifact categories. *Cognitive Psychology*, *20*(1), 65-95. https://doi.org/10.1016/0010-0285(88)90025-4

Gerlach, C., Zhu, X., & Joseph, J. E. (2015). Structural Similarity Exerts Opposing Effects on Perceptual Differentiation and Categorization : An fMRI Study. *Journal of Cognitive Neuroscience*, *27*(5), 974-987. https://doi.org/10.1162/jocn_a_00748

Gibson, J. J. (1966). *The senses considered as perceptual systems*. Houghton Mifflin.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food Security : The Challenge of Feeding 9 Billion People. *Science*, *327*(5967), 812-818. https://doi.org/10.1126/science.1185383

Graça, J., Godinho, C. A., & Truninger, M. (2019). Reducing meat consumption and following plant-based diets : Current evidence and future directions to inform integrated transitions. *Trends in Food Science & Technology*, *91*, 380-390. https://doi.org/10.1016/j.tifs.2019.07.046

Greenwald, A., McGhee, D., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition : The implicit association test. *Journal of personality and social psychology*. https://doi.org/10.1037/0022-3514.74.6.1464

Harguess, J. M., Crespo, N. C., & Hong, M. Y. (2020). Strategies to reduce meat consumption : A systematic literature review of experimental studies. *Appetite*, *144*, 104478. https://doi.org/10.1016/j.appet.2019.104478

Hoek, A. C., Luning, P. A., Weijzen, P., Engels, W., Kok, F. J., & de Graaf, C. (2011). Replacement of meat by meat substitutes. A survey on person- and product-related factors in consumer acceptance. *Appetite*, *56*(3), 662-673. https://doi.org/10.1016/j.appet.2011.02.001

Hoek, A. C., van Boekel, M. A. J. S., Voordouw, J., & Luning, P. A. (2011). Identification of new food alternatives : How do consumers categorize meat and meat substitutes? *Food Quality and Preference*, *22*(4), 371-383. https://doi.org/10.1016/j.foodqual.2011.01.008

Iriti, M., & Varoni, E. M. (2017). Pulses, Healthy, and Sustainable Food Sources for Feeding the Planet. *International Journal of Molecular Sciences*, *18*(2), 255. https://doi.org/10.3390/ijms18020255

Jallinoja, P., Niva, M., & Latvala, T. (2016). Future of sustainable eating? Examining the potential for expanding bean eating in a meat-eating culture. *Futures*, *83*, 4-14. https://doi.org/10.1016/j.futures.2016.03.006

Julia, C., Martinez, L., Allès, B., Touvier, M., Hercberg, S., Méjean, C., & Kesse-Guyot, E. (2018). Contribution of ultra-processed foods in the diet of adults from the French NutriNet-Santé study. *Public Health Nutrition*, *21*(1), 27-37. https://doi.org/10.1017/S1368980017001367

Killgore, W. D. S., Young, A. D., Femia, L. A., Bogorodzki, P., Rogowska, J., & Yurgelun-Todd, D. A. (2003). Cortical and limbic activation during viewing of high- versus low-calorie foods. *NeuroImage*, *19*(4), 1381-1394. https://doi.org/10.1016/s1053-8119(03)00191-5

Lafraire, J., Rioux, C., Hamaoui, J., Girgis, H., Nguyen, S., & Thibaut, J.-P. (2020). Food as a borderline domain of knowledge : The development of domain-specific inductive reasoning strategies in young children. *Cognitive Development*, *56*, 100946. https://doi.org/10.1016/j.cogdev.2020.100946

Lebart, Morineau, Piron. (1995). *Statistique exploratoire multidimensionnelle* (Dunod).

Lemken, D., Spiller, A., & Schulze-Ehlers, B. (2019). More room for legume – Consumer acceptance of meat substitution with classic, processed and meat-resembling legume products. *Appetite*, *143*, 104412. https://doi.org/10.1016/j.appet.2019.104412

Loughnan, S., Haslam, N., & Bastian, B. (2010). The role of meat consumption in the denial of moral status and mind to meat animals. *Appetite*, *55*(1), 156-159. https://doi.org/10.1016/j.appet.2010.05.043

Melendrez-Ruiz, J., Buatois, Q., Chambaron, S., Monnery-Patris, S., & Arvisenet, G. (2019). French consumers know the benefits of pulses, but do not choose them : An exploratory study combining indirect and direct approaches. *Appetite*, *141*, 104311. https://doi.org/10.1016/j.appet.2019.06.003

Melendrez-Ruiz, J., Chambaron, S., Buatois, Q., Monnery-Patris, S., & Arvisenet, G. (2019). A central place for meat, but what about pulses? Studying French consumers' representations of main dish structure, using an indirect approach. *Food Research International*, *123*, 790-800. https://doi.org/10.1016/j.foodres.2019.06.004

Miller, J. (1988). A warning about median reaction time. *Journal of Experimental Psychology: Human Perception and Performance*, *14*(3), 539-543. https://doi.org/10.1037/0096-1523.14.3.539

Nguyen, S. P. (2007). An apple a day keeps the doctor away : Children's evaluative categories of food. *Appetite*, *48*(1), 114-118. https://doi.org/10.1016/j.appet.2006.06.001

Nguyen, S. P., & Murphy, G. L. (2003). An Apple is More Than Just a Fruit : Cross-Classification in Children's Concepts. *Child Development*, *74*(6), 1783-1806. https://doi.org/10.1046/j.1467-8624.2003.00638.x

Osborne, J. (2002). *Notes on the use of data transformations*. *8*, 8.

Pergola, G., Foroni, F., Mengotti, P., Argiris, G., & Rumiati, R. I. (2017). A neural signature of food semantics is associated with body-mass index. *Biological Psychology*, *129*, 282-292. https://doi.org/10.1016/j.biopsycho.2017.09.001

Rebello, C. J., Greenway, F. L., & Finley, J. W. (2014). Whole Grains and Pulses : A Comparison of the Nutritional and Health Benefits. *Journal of Agricultural and Food Chemistry*, *62*(29), 7029-7049. https://doi.org/10.1021/jf500932z

Rio, C. (2017). Les légumes secs, aliments de choix à valoriser. *Cahiers de Nutrition et de Diététique*, *52*(2), 71-77. https://doi.org/10.1016/j.cnd.2016.11.006

Ross, B. H., & Murphy, G. L. (1999). Food for thought : Cross-classification and category organization in a complex real-world domain. *Cognitive Psychology*, *38*(4), 495-553. https://doi.org/10.1006/cogp.1998.0712

Rothgerber, H. (2020). Meat-related cognitive dissonance : A conceptual framework for understanding how meat eaters reduce negative arousal from eating animals. *Appetite*, *146*, 104511. https://doi.org/10.1016/j.appet.2019.104511

Rozin, P., & Fallon, A. (1980). The psychological categorization of foods and non-foods : A preliminary taxonomy of food rejections. *Appetite*, *1*(3), 193-201. https://doi.org/10.1016/S0195-6663(80)80027-4

Rumiati, R. I., & Foroni, F. (2016). We are what we eat : How food is represented in our mind/brain. *Psychonomic Bulletin & Review*, *23*(4), 1043-1054. https://doi.org/10.3758/s13423-015-0908-2

Thibaut, J.-P., Lafraire, J., & Foinant, D. (2020). A time for a meal? Children's conceptions of short-term and long-term effects of foods. *Cognitive Development*, *55*, 100885. https://doi.org/10.1016/j.cogdev.2020.100885

Tziva, M., Negro, S. O., Kalfagianni, A., & Hekkert, M. P. (2020). Understanding the protein transition : The rise of plant-based meat substitutes. *Environmental Innovation and Societal Transitions*, *35*, 217-231. https://doi.org/10.1016/j.eist.2019.09.004

Urdapilleta, I., Mirabel-Sarron, C., Eiber, R., & Richard, J.-F. (2005). What categorization tells us about food representation. *Current Psychology Letters. Behaviour, Brain & Cognition*, *17, Vol. 3, 2005*, Article 17, Vol. 3, 2005. http://journals.openedition.org/cpl/457

Vainio, A., Niva, M., Jallinoja, P., & Latvala, T. (2016). From beef to beans : Eating motives and the replacement of animal proteins with plant proteins among Finnish consumers. *Appetite*, *106*, 92-100. https://doi.org/10.1016/j.appet.2016.03.002

Vandenbroele, J., Slabbinck, H., Van Kerckhove, A., & Vermeir, I. (2019). Mock meat in the butchery : Nudging consumers toward meat substitutes. *Organizational Behavior and Human Decision Processes*. https://doi.org/10.1016/j.obhdp.2019.09.004

Virtanen, Y., Kurppa, S., Saarinen, M., Katajajuuri, J.-M., Usva, K., Mäenpää, I., Mäkelä, J., Grönroos, J., & Nissinen, A. (2011). Carbon footprint of food – approaches from national input–output statistics and a LCA of a food portion. *Journal of Cleaner Production*, *19*(16), 1849-1856. https://doi.org/10.1016/j.jclepro.2011.07.001

WARRINGTON, E. K., & SHALLICE, T. (1984). CATEGORY SPECIFIC SEMANTIC IMPAIRMENTS. *Brain*, *107*(3), 829-853. https://doi.org/10.1093/brain/107.3.829

Figure 1. Protein containing food pictures used in the two experiments.

Figure 2. Number of times a dimension was used by participants to perform the forced extraction task as a function of degree of processing (Set A: slightly processed item, Set B: highly processed item).

Figure 3. Number of times a dimension was used by participants to perform the forced extraction task as a function of condition (*i.e.,* composition of the triplets: PA-PV-UA, PA-PV-UV, UA-UV-PA, UA-UV-PV) and degree of processing (Set A: slightly processed item, Set B: highly processed item). PA: processed animal item; PV: processed plant item; UA: unprocessed animal item; UV: unprocessed plant item.

Figure 4. Number of times a dimension was used by participants to perform the forced extraction task as a function of condition (*i.e*., composition of the triplets: PA-PV-UA, PA-PV-UV), similarity (similar and dissimilar) and degree of processing (Set A: slightly processed item, Set B: highly processed item). PA: processed animal item; PV: processed plant item; UA: unprocessed animal item; UV: unprocessed plant item.

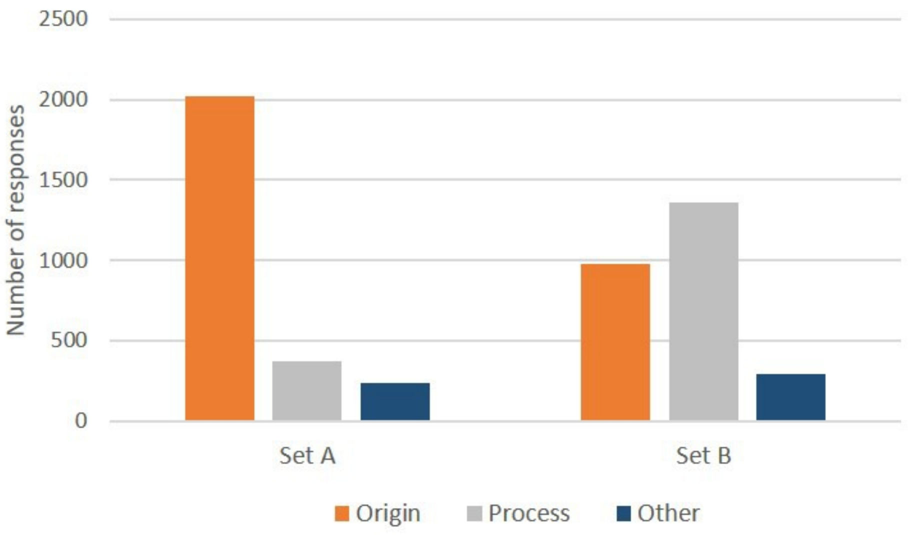
Figure 5. DistatisR positioning maps (Dimension 1 and 2) of items with confidence ellipses (95%), Set 1 (left) and Set 2 (right). The point size is proportional to the contribution to the axes. Each picture is labelled with letters and number after underscore. The letters correspond to UA - unprocessed meat, UV - legumes and cereals, PA1 - processed meat (steak and sausages), PV1 - processed legumes and cereals (patties and sausages), PA2 - ready-to-eat dishes with meat (pasta and couscous box) and PV2 - ready-to-eat dishes without meat (pasta and couscous box). The number identify the picture (see figure 1 for correspondence).

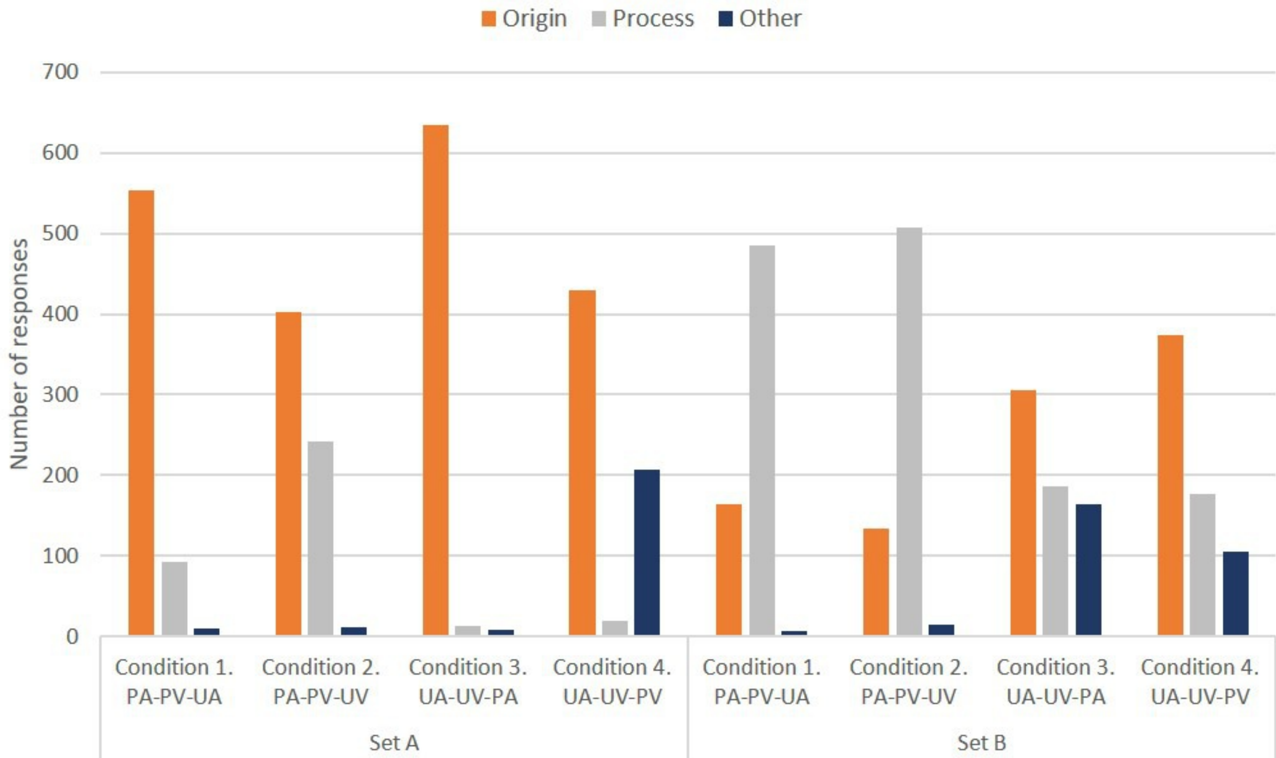
Figure 6. DistatisR positioning maps (Dimension 1 and 3) of items with confidence ellipses (95%), Set 1 (left) and Set 2 (right). The point size is proportional to the contribution to the axes. Each picture is labelled with letters and number after underscore. The letters correspond to UA - unprocessed meat, UV - legumes and cereals, PA1 - processed meat (steak and sausages), PV1 - processed legumes and cereals (patties and sausages), PA2 - ready-to-eat dishes with meat (pasta and couscous box) and PV2 - ready-to-eat dishes without meat (pasta and couscous box). The number identify the picture (see figure 1 for correspondence).

Figure 7. Property clouds for each category. Categories with animal-based items on the left and categories with plant-based items on the right. UA - unprocessed meat, UV - legumes and cereals, PA1 - processed meat (steak and sausages), PV1 - processed legumes and cereals (patties and sausages), PA2 - ready-to-eat dishes with meat (pasta and couscous box) and PV2 - ready-to-eat dishes without meat (pasta and couscous box).

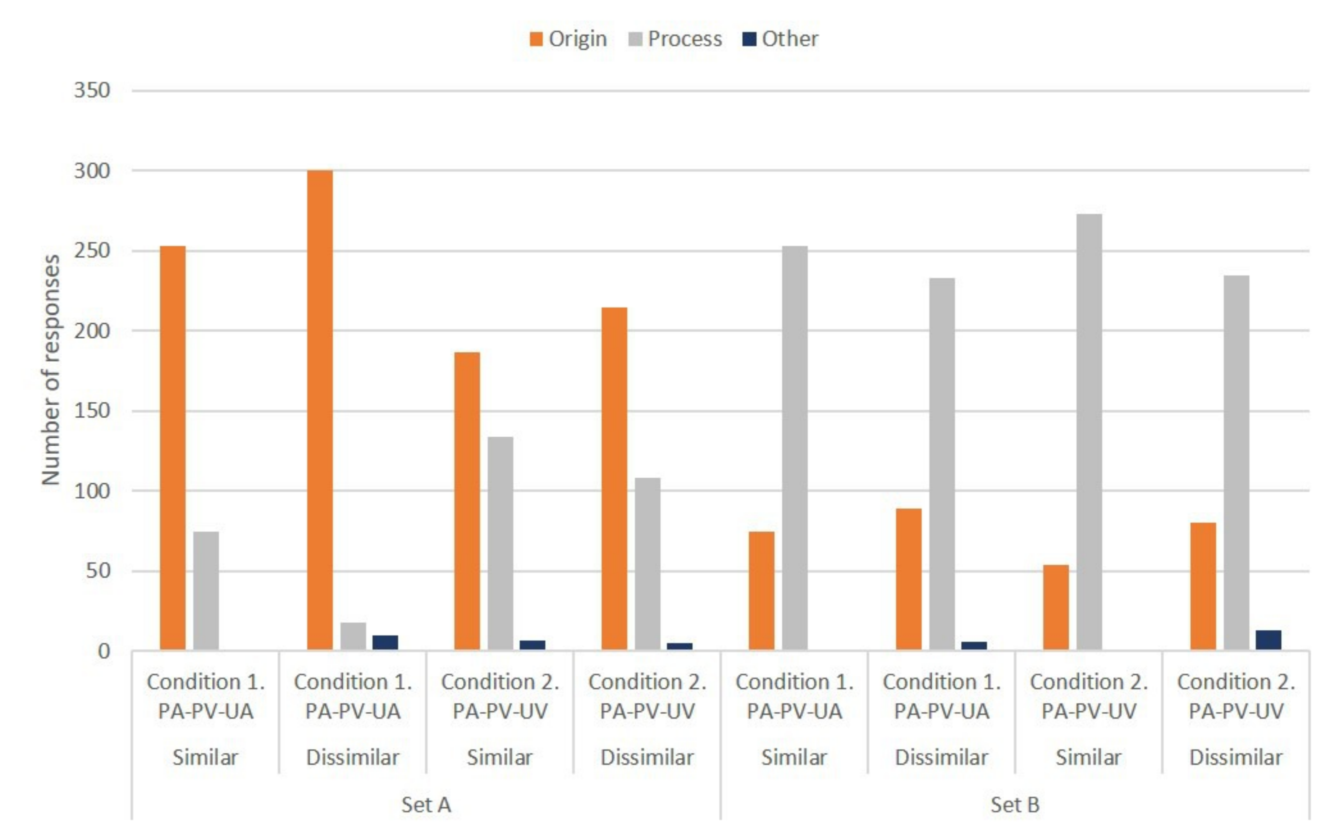
Figure 8. CA map of property generation. Categories with animal items are in red and categories with plant items are in green. The dotted lines connect the categories with the same degree of process. UA - unprocessed meat, UV - legumes and cereals, PA1 - processed meat (steak and sausages), PV1 - processed legumes and cereals (patties and sausages), PA2 - ready-to-eat dishes with meat (pasta and couscous box) and PV2 - ready-to-eat dishes without meat (pasta and couscous box).

Category 1: UA Unprocessed Meat	 UA - 1, UA - 2, UA - 3, UA - 4, UA - 5, UA - 6, UA - 7, UA - 8 UA - 9, UA - 10, UA - 11, UA - 12, UA - 13, UA - 14, UA - 15, UA - 16
Category 2: UV Legumes & Cereals	 UV - 1, UV - 2, UV - 3, UV - 4, UV - 5, UV - 6, UV - 7, UV - 8 UV - 9, UV - 10, UV - 11, UV - 12, UV - 13, UV - 14, UV - 15, UV - 16
Category 3: PA1 Processed Meat (steaks & sausages)	 PA1 - 1, PA1 - 2, PA1 - 3, PA1 - 4, PA1 - 5, PA1 - 6, PA1 - 7, PA1 - 8
Category 4: PV1 Processed legumes & Cereals (patties & sausages)	 PV1 - 1, PV1 - 2, PV1 - 3, PV1 - 4, PV1 - 5, PV1 - 6, PV1 - 7, PV1 - 8
Category 5: PA2 Ready-to-eat dishes with meat (pasta-couscous box)	 PA2 - 1, PA2 - 2, PA2 - 3, PA2 - 4, PA2 - 5, PA2 - 6, PA2 - 7, PA2 - 8
Category 6: PV2 Ready-to-eat dishes without meat (pasta-couscous box)	 PV2 - 1, PV2 - 2, PV2 - 3, PV2 - 4, PV2 - 5, PV2 - 6, PV2 - 7, PV2 - 8

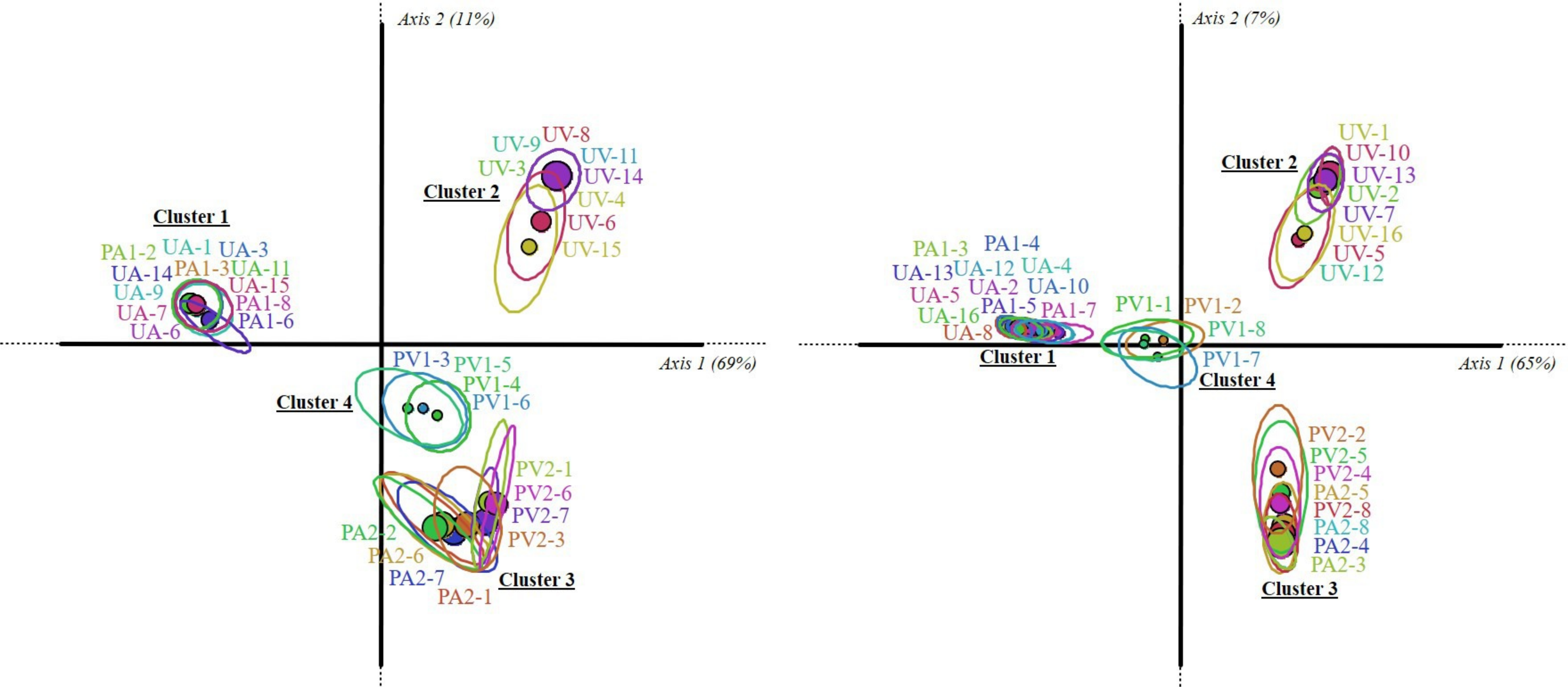

2500
2000
1500
1000
500
0
Number of responses
Set A
Set B
Origin
Process
Other

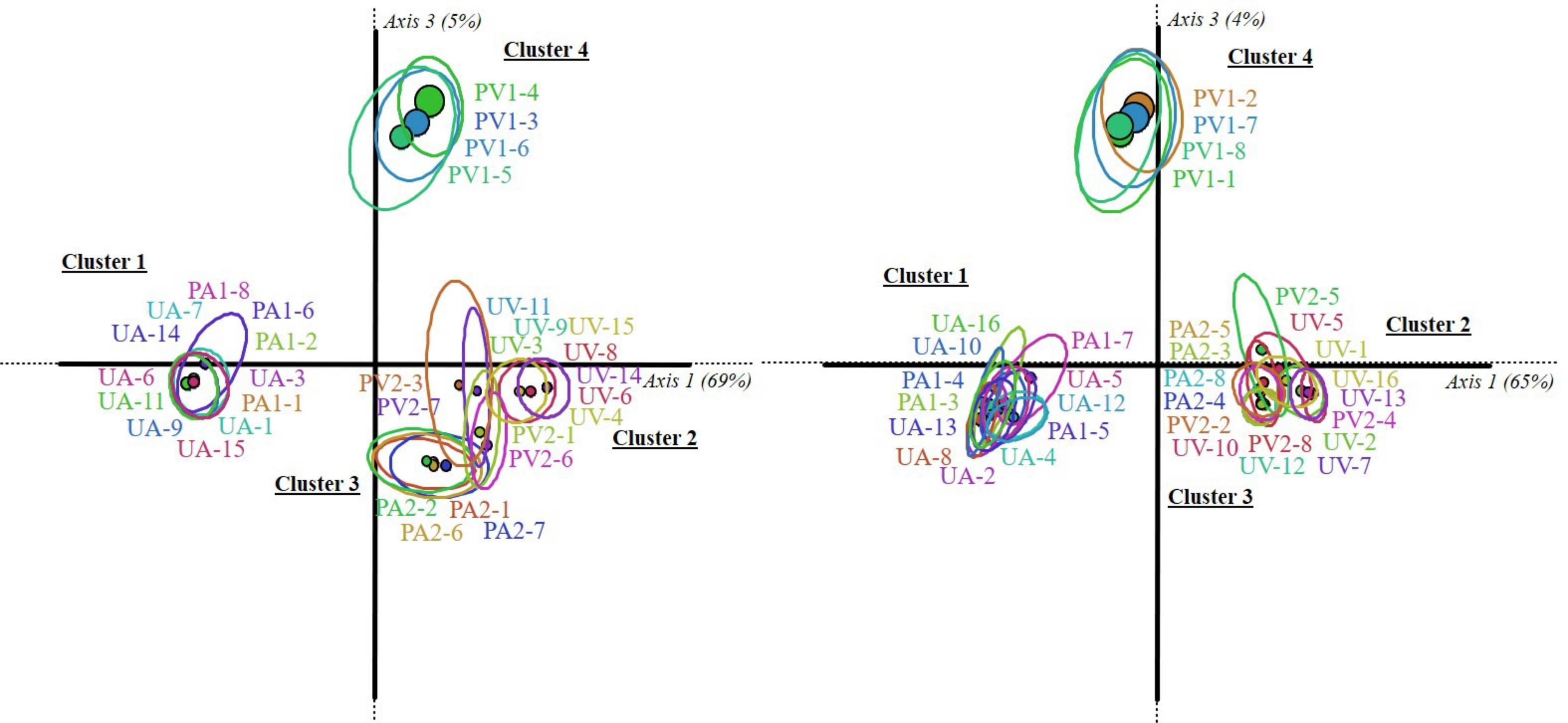


Origin
Process
Other
700
600
500
400
300
200
100
0
Number of responses
Condition 1. PA-PV-UA
Condition 2. PA-PV-UV
Condition 3. UA-UV-PA
Condition 4. UA-UV-PV
Set A
Condition 1. PA-PV-UA
Condition 2. PA-PV-UV
Condition 3. UA-UV-PA
Condition 4. UA-UV-PV
Set B



Origin
Process
Other
350
300
250
200
150
100
50
0
Number of responses
Condition 1.
PA-PV-UA
Similar
Condition 1.
PA-PV-UA
Dissimilar
Condition 2.
PA-PV-UV
Similar
Condition 2.
PA-PV-UV
Dissimilar
Condition 1.
PA-PV-UA
Similar
Condition 1.
PA-PV-UA
Dissimilar
Condition 2.
PA-PV-UV
Similar
Condition 2.
PA-PV-UV
Dissimilar
Set A
Set B


Axis 2 (11%)
Axis 1 (69%)
Cluster 1
PA1-2
UA-1
UA-3
UA-14
PA1-3
UA-11
UA-9
UA-15
PA1-8
UA-7
PA1-6
UA-6
Cluster 2
UV-9
UV-8
UV-11
UV-3
UV-14
UV-4
UV-6
UV-15
Cluster 4
PV1-3
PV1-5
PV1-4
PV1-6
Cluster 3
PV2-1
PV2-6
PV2-7
PV2-3
PA2-2
PA2-6
PA2-7
PA2-1
Axis 2 (7%)
Axis 1 (65%)
Cluster 2
UV-1
UV-10
UV-13
UV-2
UV-7
UV-16
UV-5
UV-12
PA1-3
PA1-4
UA-13
UA-12
UA-4
UA-5
UA-2
UA-10
UA-16
PA1-5
PA1-7
UA-8
Cluster 1
PV1-1
PV1-2
PV1-8
PV1-7
Cluster 4
PV2-2
PV2-5
PV2-4
PA2-5
PV2-8
PA2-8
PA2-4
PA2-3
Cluster 3



Axis 3 (5%)
Cluster 4
PV1-4
PV1-3
PV1-6
PV1-5
Cluster 1
PA1-8
UA-7
PA1-6
UA-14
PA1-2
UA-6
UA-3
UA-11
PA1-1
UA-9
UA-1
UA-15
UV-11
UV-9
UV-15
UV-3
UV-8
PV2-3
UV-14
Axis 1 (69%)
PV2-7
UV-6
UV-4
PV2-1
Cluster 2
PV2-6
Cluster 3
PA2-2
PA2-1
PA2-6
PA2-7
Axis 3 (4%)
Cluster 4
PV1-2
PV1-7
PV1-8
PV1-1
Cluster 1
PV2-5
UV-5
Cluster 2
UA-16
PA2-5
UA-10
PA1-7
PA2-3
UV-1
PA1-4
UA-5
PA2-8
UV-16
Axis 1 (65%)
PA1-3
UA-12
PA2-4
UV-13
UA-13
PA1-5
PV2-2
PV2-4
UA-8
UA-4
UV-10
PV2-8
UV-2
UA-2
UV-12
UV-7
Cluster 3

UA

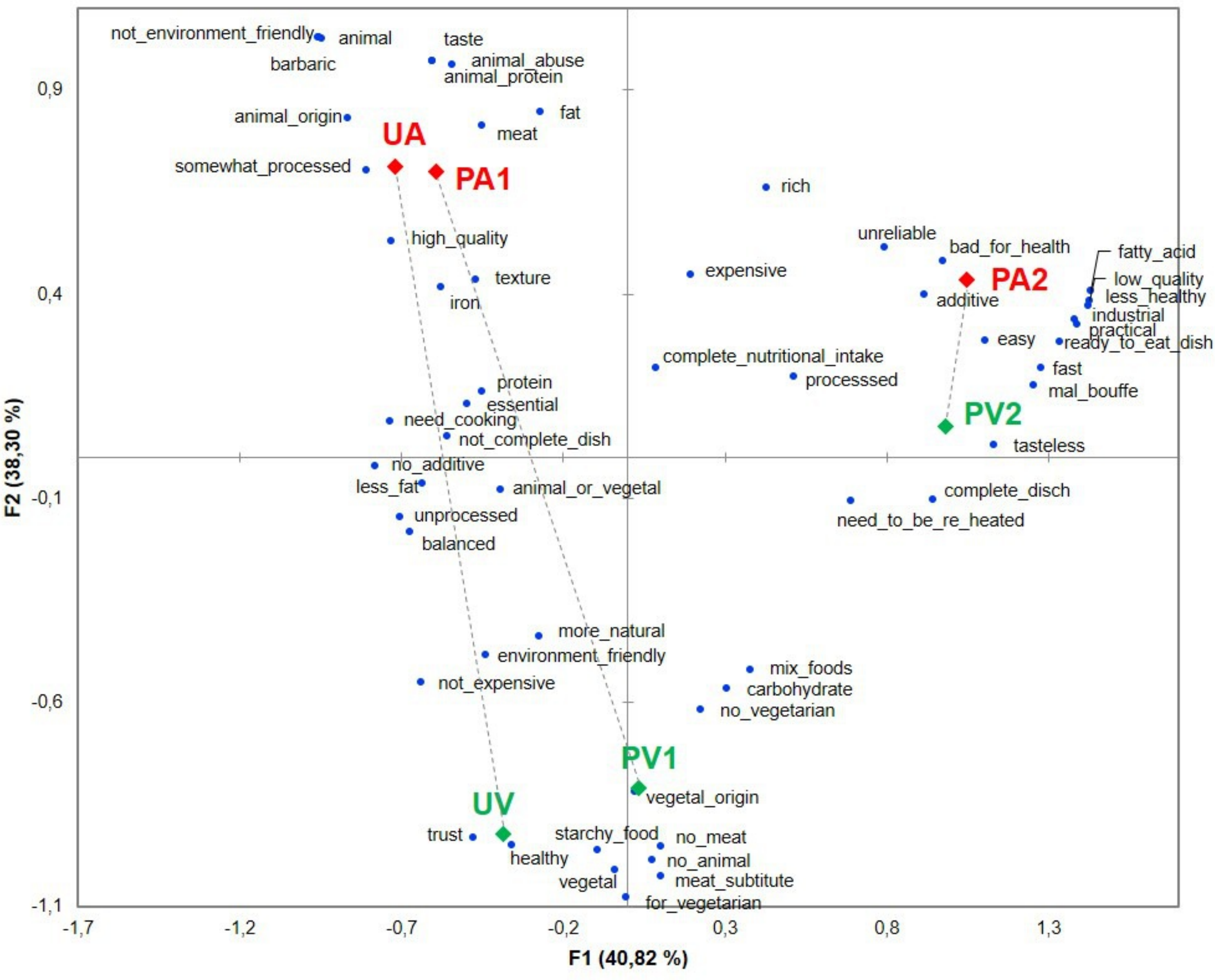
UV

PA1

PV1

PA2

PV2


not_environment_friendly
animal
taste
barbaric
animal_abuse
animal_protein
animal_origin
fat
meat
UA
somewhat_processed
PA1
rich
high_quality
unreliable
bad_for_health
fatty_acid
expensive
PA2
low_quality
texture
less_healthy
additive
iron
industrial
practical
easy
ready_to_eat_dish
complete_nutritional_intake
fast
processsed
protein
mal_bouffe
essential
need_cooking
PV2
not_complete_dish
tasteless
no_additive
less_fat
animal_or_vegetal
complete_disch
need_to_be_re_heated
unprocessed
balanced
more_natural
environment_friendly
mix_foods
not_expensive
carbohydrate
no_vegetarian
PV1
vegetal_origin
UV
trust
starchy_food
no_meat
healthy
no_animal
vegetal
meat_subtitute
for_vegetarian
0,9
0,4
-0,1
-0,6
-1,1
F2 (38,30 %)
-1,7
-1,2
-0,7
-0,2
0,3
0,8
1,3
F1 (40,82 %)