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Pivot© profile: A new descriptive method based on free description

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ABSTRACT

The Pivot© profile is a new frequency-based descriptive method based on free description allowing to record judges' free expression in an ordinal manner. The strategy implemented in Pivot© profile to capture the relative meaning of descriptors, is to collect a free description of the differences between two products: a target product and a pivot (i.e., a product that will serve as a standard to describe the other products). The repetition of this task using the same product as the pivot, allows supplying a complete description of the set of products. A real life example on champagne showed that Pivot© profile is easy to perform for participants and allows generating meaningful product descriptions. Simulations indicated that the approach is robust for both the choice of the pivot among the products of interest and the heterogeneity of the panel. Both experimental data and simulations highlight the potential of the Pivot© profile. Pros and cons on both experimental and theoretical aspects are discussed comparatively to other fast descriptive methods.

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1. Introduction

Descriptive analysis is a base tool for food sensory scientists involving the specification of the perceivable characteristics of a product via an *ad hoc* lexicon generated by a panel of typically eight to 15 panelists. Panelists are selected on their sensory abilities and trained to reach a consensus on the meaning of each descriptor or attribute in the lexicon and to perform intensity rating in a consensual and reliable way. To some extent, panelists are considered as measuring instruments. As pointed out by Campo, Ballester, Langlois, Dacremont, and Valentin (2010) "descriptive analysis is well adapted when applied to simple products, but is less suited to profile complex products, especially when dealing with odors". In line with this assertion recent neuro-physiological developments indicate that olfactory perception is characterized by great genetic variations. According to Menashe, Man, Lancet, and Gilad (2003) among the 1000 human olfactory receptor genes more than 50% are pseudo genes. This high proportion of non-operating genes is the reason for a great genotypic variation. Among 189 studied individuals and taking into consideration only 26 coding zones of olfactory receptors, Menashe et al. (2003) could not find anyone having the same genotypic profile. This strong inter-individual variability is also observed at the gustatory level as described by Faurion (1989). For example, according to this author the detection threshold for the sweetness of sucrose varies from a factor of 1 to 3 in concentration for 60% of the population and from a factor from 1 to 10 for the extremes. Besides inter-individual variability, chemo-perception is prone to intra-individual variability resulting in different responses for the same person to the same question (Sauvageot, 1998). Because of this large inter and intra-individual variability conventional descriptive analysis (DA) requires extensive training before the panel reaches an agreement on the meaning of attributes and assesses attribute intensities in a reliable way. An approach taking into account individual differences in terms of both perception and expression of this perception might thus be better adapted to describe complex products than standard DA.

Several alternatives have been described in the literature. Free choice profile (Williams & Langron, 1984) and the Repertory grid method (Thomson & McEwan, 1988) were the first ones. They both allow participants to use their own personal attributes to describe the products. However, they also involve a monadic intensity rating of the attributes that might require some training to be performed in a reliable way. To overcome this limit, other approaches were reported: labeled free sorting (Lawless, Sheng, & Knoops, 1995), Projective mapping (Risvik, McEwan, Colwill, Rogers, & Lyon, 1994), Napping® (Pagès, 2003), Flash profile (Sieffermann, 2000), Ultra flash profile (Perrin et al., 2008), Check-all-that-apply (CATA) (Adams, Williams, Lancaster, & Foley, 2007; Lancaster & Foley, 2007). Although these methods have been used successfully to describe a range of products (for a review see Valentin, Chollet, Lelièvre, & Abdi, 2012; Varela & Ares, 2012) the temporal dimension is rarely taken into consideration and, except for CATA, the whole set of products needs to be presented simultaneously. To bypass this last problem, Polarized Sensory Positioning (PSP), a descriptive method recently introduced in the sensory evaluation toolbox (Teillet, Schlich, Urbano, Cordelle, & Guichard, 2010), proposes to compare the set of products to be described to three known stable reference products. The main drawback of this method is to provide indirect descriptions of the product via the description of the known references.

In this paper we present a new reference-based approach, the Pivot© profile (noted PP, Thuillier, 2007) derived from the free description method. The free description method, popular among wine professionals, requires asking participants to describe all what they perceive without any constraint. This method does not need any reference, does not impose any descriptor or scale and involves a monadic sequential presentation of the samples. Data analysis calls upon textual analysis techniques which are often difficult to implement, time consuming and give rise to a crude description of each product. PP is an improvement over free description that allows for recording participants' free expressions in an ordinal manner. It has the advantage of providing a precise and detailed wording of perception at the hedonic, qualitative and quantitative levels and can be used, a priori, by experts as well as consumers.

Most of the time, free descriptions do not include mere descriptors but an association between a descriptor and a quantifier or degree modifier (e.g., "not", "slightly", "very much", etc.) even in monadic descriptions (Giboreau, Dacremont, Guerrand, & Dubois, 2009). A difficult step of free description transcoding is dealing with these degree modifiers. This step has to be considered with attention as grouping "sweet" and "not sweet" together would be obviously misleading. However, on the other hand, keeping every degree modifier would lead to a multiplicity of expressions (each word – quantifier association such as "slightly sweet", "a little bit sweet", "moderately sweet", etc. being considered as different descriptors) that would "inflate" both the total number of descriptors considered for analysis and the number of descriptors with low citation frequencies. This approach makes data more noisy and the analysis less powerful. The strategy implemented in PP to capture the relative meaning of the descriptors is to collect free descriptions of the differences between two products: a target product and a pivot. The pivot product is chosen within the range of products to be evaluated to serve as a standard to describe the other products. The description takes the form of "less *X*" or "more *Y*" than the pivot (e.g., less sweet, more astringent, etc.). In this respect, PP allows for suppressing or at least drastically limiting the use of degree modifiers. This strategy has the advantage of preserving individual expressions reflecting the specific perception of each of the participants, while decreasing de facto the importance of the specific and individual forms of description and expression by each of the participants. The dynamic repetition of this exercise, using the same product as the pivot, provides a complete description of the set of products.

An application of the method to describe champagnes with enologists is first presented. The described champagnes are made with different proportions of grape varieties and aged wine, each promoting specific sensory characteristics. This allows for checking both the ability of professionals enologists to use such an approach and the ability of the method to produce relevant descriptions. This is assessed by comparing obtained descriptions to sensory characteristics expected from champagne composition. However, knowing the physical properties of a product is not enough to fully predict the perception of this product by the taster. Thus, modeling is also used for studying the impact of critical parameters i.e., the choice of the pivot product and the heterogeneity of the panel, on the obtained results.

2. Application of PP

2.1. Materials and method

2.1.1. Panel

The panel included three female and 10 male participants (average age: 45 years old). All of them were wine professionals with a great experience in champagne evaluation (winemakers, oenologists) working in champagne wine companies in Reims (Champagne region, France).

2.1.2. Wines

Six champagnes freely supplied by six Champagne producers were used in this study. Table 1 presents their composition in terms of proportions of Chardonnay (white grape), Pinot Noir, and Pinot Meunier (red grapes) the three major grape varieties in Champagne, and "reserve wine" (aged wine) that ensure a consistent style to non-vintage Champagne. For each champagne, 70 ml of wine was served in transparent INAO® standard glasses.

2.1.3. Procedure

The evaluation was organized in a single session in a sensory room in Reims. The evaluation was structured on a temporal basis going from observation to in-mouth perceptions. Wine Ch6 was used as pivot. The other five wines (Ch1–Ch5) were presented in random order each one in simultaneous presentation with the pivot. For each pair of wines (one sample and the pivot), participants were asked to write down all the attributes they perceived in the sample in lower or higher intensity compared to the pivot (e.g., less sweet, more astringent, etc.). Judges were instructed to use only descriptive words without any sentence. The negative form was not allowed (e.g., flat should be used instead of non-effervescent) as two samples cannot be compared on characteristics which are not present (e.g. Product A is less non-effervescent than Product B). An example of answer form is given Fig. 1.

2.1.4. Data analysis

Data analysis begins by listing all the generated words from the answer forms. One hundred and twenty-six forms were generated. They were grouped by semantic categories by one experimenter sharing the same kind of expertise as the participants (wine professional). For instance, the words: *aromatic*, *expressive*, *pronounced*, *present*, and *powerful* were all considered as synonymous with *intense*. This grouping led to 16 semantic groups (Table 2) validated by the experts involved in the evaluation. From these groups a synonym dictionary was constructed in Tastel© software. Then, the number of times each attribute is cited as "less than the pivot" (negative frequency) and "more than the pivot" (positive frequency) for each wine were automatically counted up (Table 2). Next, the negative frequencies were subtracted from the positive frequencies. The resulting scores provide an estimation of the intensity; the larger the number of participants that found the sample "more" than the pivot compared to the number of participants that found the sample "less" than the pivot, the higher the intensity of this attribute in this sample. For instance, for Ch1, the positive and negative frequencies for *intensity* are respectively 5 and 4, thus Ch1 was equally judged more intense and less intense

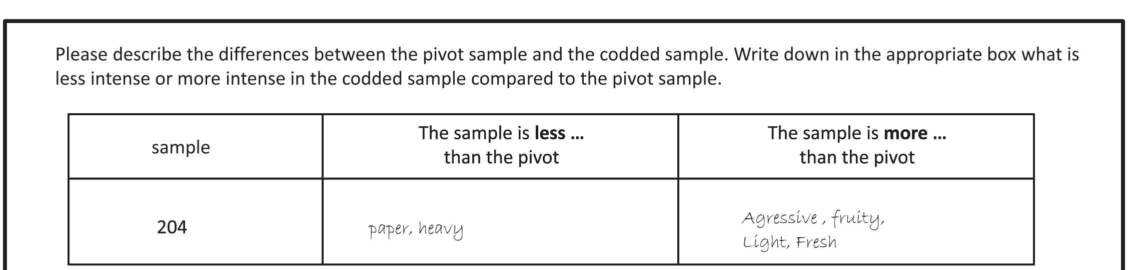
Table 1
Grape composition and vintage of champagnes.

	Pinot Noir (%)	Pinot Meunier (%)	Chardonnay (%)	Reserved wine (%)	Bottling
Ch1	60	0	40	25	2002
Ch2	53	18	29	33	2002
Ch3	36	18	46	48	1998
Ch4	40	40	20	37	2003
Ch5	50	15	35	20	2003
Ch6 (pivot)	0	0	100	0	2003

Table 2
Example of data analysis for Champagne 1.

Product	Attribute	Positive frequency	Negative frequency	Difference positive – negative	Translated frequency
Ch1	Intense	5	4	1	5
Ch1	Fruity	1	3	−2	2
Ch1	Maturity	6	0	6	10
Ch1	Complex	3	0	3	7
Ch1	Fresh	1	3	−2	2
Ch1	Pungent	4	1	3	7
Ch1	Floral	1	0	1	5
Ch1	Roasted	1	0	1	5
Ch1	Fine	1	0	1	5
Ch1	Paper	0	2	−2	2
Ch1	Citrus	0	1	−1	3
Ch1	Reduced	0	0	0	4
Ch1	Butter	0	0	0	4
Ch1	Tertiary	2	0	2	6
Ch1	Closed	0	0	0	4
Ch1	Vegetal	1	1	0	4
Ch2	Intense	4	3	1	5

For each attribute, negative frequency and positive frequency give the number of participants that reported the sample Ch1 was "less" or "more" that the pivot; the translated frequency is the "difference positive – negative" plus 4, as the lowest value of the difference column (whatever the attribute and the sample) was −4 (not shown here).


Please describe the differences between the pivot sample and the codded sample. Write down in the appropriate box what is less intense or more intense in the codded sample compared to the pivot sample.

sample	The sample is **less** ... than the pivot	The sample is **more** ... than the pivot
204	paper, heavy	Agressive, fruity, Light, Fresh

Fig. 1. Example of questionnaire filled in by participants.

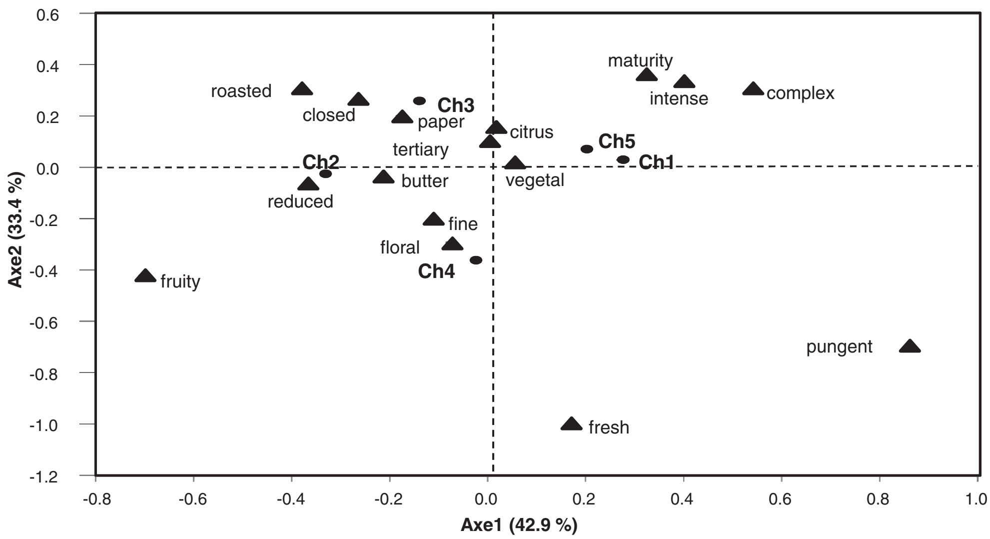


Fig. 2. Projection of champagnes (Ch1–Ch5) in the CA map (subspace 1–2).

than the pivot indicating that the intensity of this sample was actually close to the intensity of the pivot. By contrast, the positive and negative frequencies for *maturity* are respectively 6 and 0, indicating that Ch1 was clearly judged more mature than the pivot. Last, the resulting scores are translated so as to obtain positive scores only. This was done by adding the absolute value of the minimum score to all the scores. The minimum score thus takes on the value of zero and all other scores are positive. The detail procedure is also explained in the Appendix Section A2.2. The translated scores were compiled in a wines $\times$ attributes matrix which was then submitted to a Correspondence Analysis (CA) to obtain a product map. All attributes were kept for the analysis as only a few attributes showed low citation frequencies. The analysis was performed using XLStat 2013 (Addinsoft, Paris, France).

2.2. Results

For simplicity sake, only the data collected by smell are presented here. The complete analysis can be found in Thuillier, 2007. The first two dimensions of the CA (Fig. 2) explain about 76% of the total variance. Two groups of wines can be identified: Ch1, Ch3, and Ch5, on the one hand, characterized by *maturity*, *intense* and *complex* notes and, on the other hand, Ch2 and Ch4 described by *floral* and *fruity* notes.

2.3. Discussion

PP allows for a description of complex products such as wines where a tradition of free description is relatively strong among experts. Descriptions are coherent with wine compositions. Ch1, Ch3, and Ch5 described by "maturity" include a higher proportion of reserve wine in the blend than the two others and the pivot. Reserve wine is known to promote maturity notes such as dry fruits, honey, brioche, or toasted. Ch2 and Ch4 described by "fruity" include a larger proportion of Pinot Noir and Pinot Meunier in the blend than the pivot (100% Chardonnay). Pinot Noir and Pinot Meunier are known to promote more fruity notes (white fruits, red fruits, and black fruits) whereas Chardonnay usually brings some freshness and citrus notes.

At the end of the session, participants reported that they feel this method was less demanding than free description. Thus, this method might provide a trade-off between experts' practice and sensory evaluation methods. It might prove also useful for other products because it allows for a fast direct description of the products with the possibility of aggregating data over sessions as long as a stable reference is available. However, the main difficulty remains the choice of the pivot product. In the next section, we evaluate the effect of the choice of the pivot and the impact of panel heterogeneity on product descriptions, using a modeling approach.

3. Modeling

3.1. General principle

The modeling approach is inspired by the work of Chou, Paplinski, and Gustafsson (2007) on self-organized neuronal networks that model the neuronal mapping of Chinese phonemes. The main characteristics of the Chou et al. (2007) model are to take into account the morphologic similarities among phonemes and the inter-individual variability in phoneme pronunciation. Phonemes are bimodal percepts combining written and auditory information. They can be represented on two 2-D maps according to their similarities either based on written sign morphology or on auditory characteristics. Then, similarities of bimodal percepts are represented by a combination of these two maps. The bimodal representation is very robust to disturbance in one modality. Even though different speakers would not pronounce phonemes in the

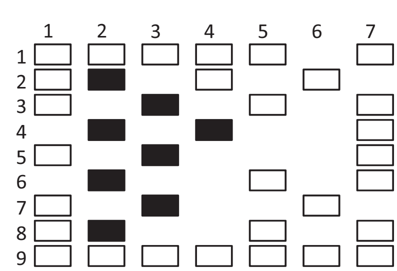


Fig. 3. Lexicon represented as words (rectangles) in a 7 $\times$ 9 matrix. The lexicon includes 37 words denoted w_{ij} (with *i*: line number; *j*: column number). The description of one product is symbolized by a subset of adjacent words of the lexicon called core description. Black squares represent the core description of Product 1. By analogy to descriptive analysis, it would represent the sub-set of descriptors with non-nil intensity, among an attribute list of 37 descriptors, of the product description generate by the panel.

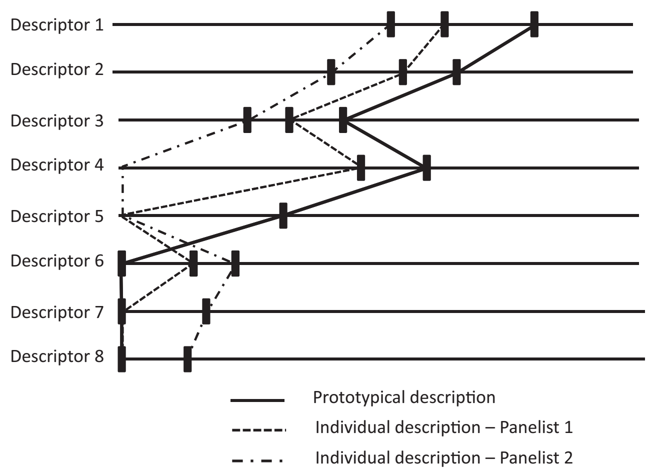


Fig. 4. Theoretical examples of individual descriptions generated from a prototypical description; panelist 2 showed a higher distortion level compared to panelist 1.

same way, percepts could still be easily identified. We transposed these ideas to model descriptive panel output when describing a set of products. Products are described by associations of attributes and degree modifiers (such as phonemes combine auditory and visual information). We considered that panelists express their perceptions using a common lexicon and shared semantic rules. Words of the lexicon refer to perceived features or sensory properties of the products. They are organized according to a semantic network in which words are more or less closely related to each other according to their meaning (in the way phonemes are mapped according to their similarities). The lexicon includes 37 words represented as cells in a 7×9 matrix (Fig. 3) derived from the neural map of Chinese phonemes in the inspiring paper of Chou et al. (2007). Each word is noted w_{kl}, k and l indicating respectively the row and the column were the word is located.

The description of one product by one participant is symbolized by a list of related words, each one associated to a degree modifier. For modeling purpose, degree modifiers are not words but numeric values from 0 (representing "not at all") to 1 (representing "very much"). Individual descriptions are produced by distortions of a prototypical description (such as each speaker has his/her own way to pronounce phonemes introducing some inter-individual variability). The prototypical description of a product is given by a list of core attributes that are adjacent cells in the matrix representing the lexicon (Fig. 3), associated to a degree modifier set at one by definition.

If we transpose this idea to product description using the free profile approach, words and degree modifiers would be descriptors and associated intensities respectively. The prototypical description, then, could represent the product description obtained when data from the panel are aggregated. Individual descriptions (i.e., descriptions given by each participant) are more or less divergent from the aggregated panel description. This is illustrated Fig. 4 representing both the panel description and the descriptions of two participants. The departure of an individual description from the panel description can be more or less important according to the panelists. Some panelists (such as panelist 1 on Fig. 4) are quite consensual and produce description similar to the panel description whereas others (such as panelist 2 on Fig. 4) produce descriptions more divergent.

Each panelist is characterized by her/his departure from the prototypical description. This is represented in the modeling by some distortion parameters representing how much each panelist is consensual with the prototypical description. The distortion can occur at two levels: the set of words and the associated degree modifiers. From the prototypical description, one panelist may omit some words and add others. These variations are meant to reflect perceptual (e.g., some features are not perceived or are not attended to) as well as linguistic (e.g., use of synonyms or antonyms) inter-individual differences.

Transposed to the example presented on Fig. 4, the distortion of individual descriptions lay on the descriptors used: some important features of the aggregated description are not reported (such as descriptors 4 and 5 for panelists 2) but other sensory characteristics are (descriptors 6, 7, and 8). The distortion also refers to reported intensities that can be more or less close to those of the aggregated description. Thus, the higher the distortion level, the larger the discrepancy between aggregated and individual descriptions. On Fig. 4, panelist 2 has a higher distortion level compared to panelist 1.

The modeling algorithm includes two steps (Fig. 5). For each participant and each product, a description (referred to as individual description) is simulated from a prototypical description (the same for every participant) and distortion parameters (specific to each participant). Then, for each participant, the individual description of each product is compared to the description of the pivot product to simulate the response of this participant when performing a PP. Full modeling details are given in Appendix A.

For each simulation, we considered a panel of 12 panelists and six products. The prototypical descriptions of the products are kept constant for every simulation. The six prototypical descriptions considered in the simulations are given in Appendix A and the CA map derived from the product $\times$ words matrix is given in Fig. 6.

Each panel includes 12 panelists varying in terms of distortion to account for inter-individual differences among panelists. The distortion level of each panelist is determined by four parameters: the proportion of core attributes included in the individual description, the intensity level associated to the core attributes, the proportion of secondary attributes (other than the core attributes) included in the individual description, and the intensity level associated to the secondary attributes.

To estimate the stability of descriptions across pivot products, three products among the six are alternatively considered as pivot; the panel characteristics are kept constant. To estimate the effect of panel heterogeneity on the descriptions, four panels are generated; the pivot product is kept constant.

3.2. Stability of PP across pivot products

3.2.1. Method

Three products P1, P3, and P5 widely spread over the CA map based on prototypical descriptions (Fig. 6), are alternatively tested as pivot product. In the prototypical descriptions, the mean proportion of common attributes with the other products is: 0.52, 0.33, and 0.42 for P1, P3, and P5 respectively. This indicates that P1 is more "central" than P5, which is in turn more "central" than P3 in the product space.

All simulations (one for each pivot product) are run using the descriptions of Panel 1 (its characteristics in terms of distortion are given in Table A2 of Appendix A). A CA is run on each generated frequency matrix using XLStat 2013 (Addinsoft, Paris, France). RV coefficients (Robert & Escoufier, 1976) are computed on the coordinates of the products including the four axes of the CA space, using FactoMineR (Lê, Josse, & Husson, 2008) in R language (R Development Core Team, 2007).

3.2.2. Results

CA maps derived from the simulated PP with three different pivot products are presented Fig. 7.

To evaluate the stability of PP, we compared the CA spaces obtained for (1) the prototypical descriptions (Fig. 6), and (2) the

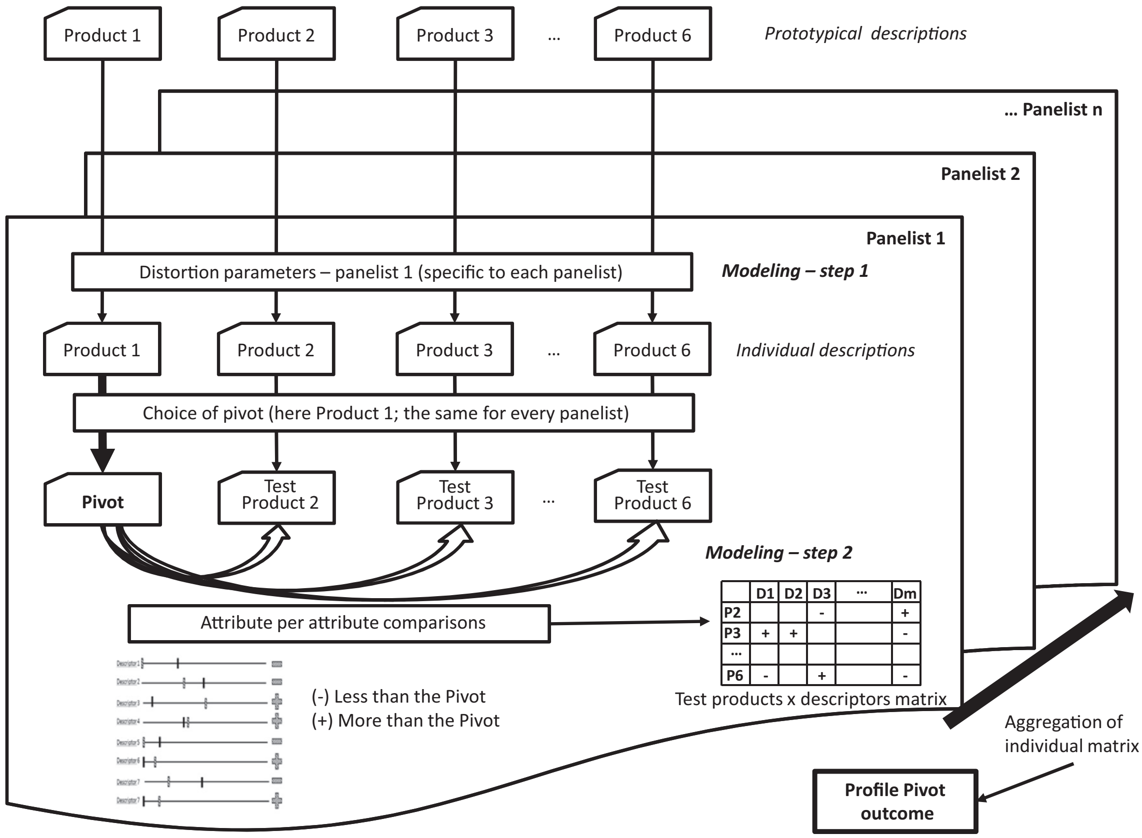


Fig. 5. Flowchart of the simulation process for one panel.

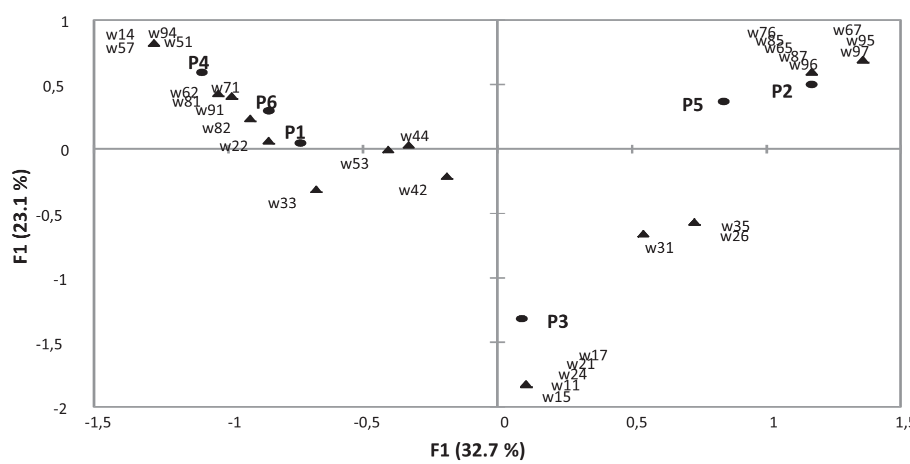


Fig. 6. Projection of the six products in the CA map (subspace 1–2) obtained from prototypical descriptions.

descriptions obtained with each of the three pivots (Fig. 7), using RV coefficients. RV coefficients computed between the CA space of the prototypical descriptions and the CA space of each of the three pivots range from 0.81 to 0.85 indicating that the product spaces are not exactly matched but still share a large part of common structure. The difference observed between the prototypical description and PP descriptions might reflect the fact that PP description is orientated by specific characteristics of the product chosen as pivot.

The RV coefficients computed across the three CA spaces obtained with each of the 3 pivots range from 0.834 (pivots P1 vs. P5) to 0.918 (pivots P1 vs. P3). The number of attributes the pivot product shares with the other products does not seem a major issue for the choice of the pivot. P1 shares the most attributes whereas P5 shares the least attributes with the other products; still they lead to highly correlated CA spaces when used as pivot. All together, these results would indicate that the choice of the pivot product is not a critical issue in the PP at least with descriptions presenting moderate degree of diversity as in this simulation.

3.3. Impact of the panel heterogeneity

3.3.1. Method

Panel heterogeneity is simulated by manipulating the distortion level of individual descriptions of the panelists. Among the four

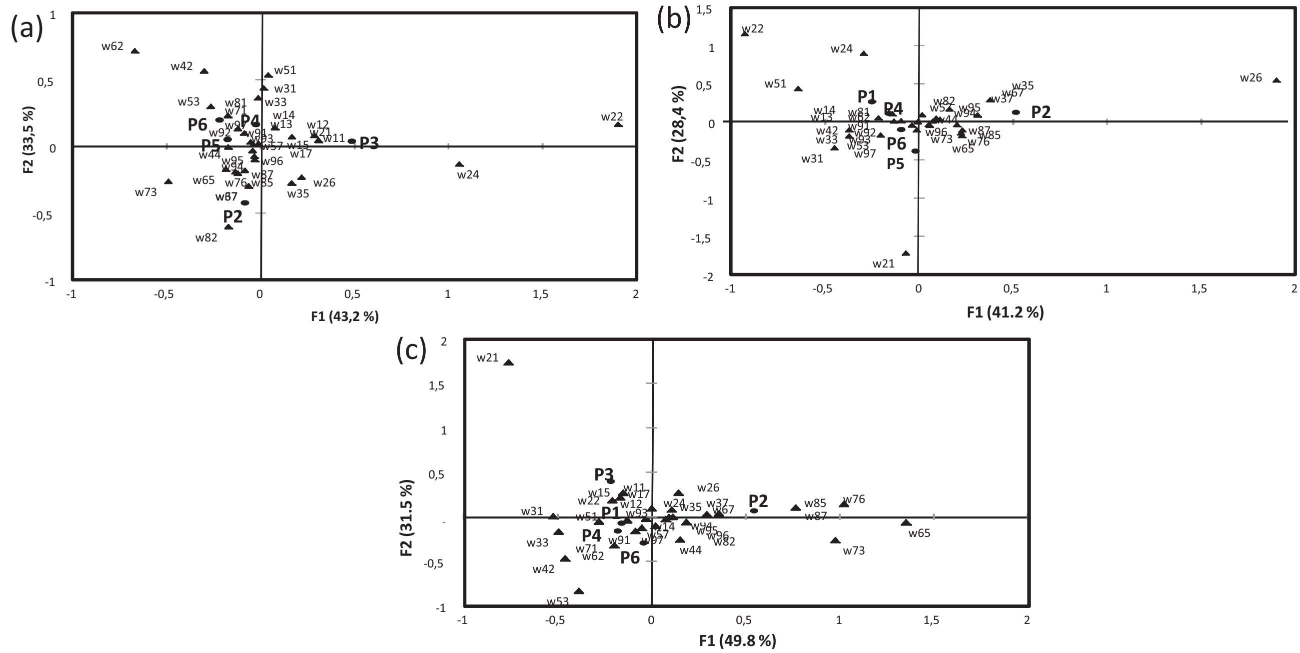


Fig. 7. Projection of the products in the CA map (subspace 1–2) obtained from simulation for three pivot products. The pivot product is (a) Product 1; (b) Product 3; (c) Product 5.

Table 3
Mean values and dispersions of P^c (proportion of core attributes included in the description) for the four panels.

Panel	Mean P^c values	STD of P^c values
1	0.700	0.135
2	0.775	0.089
3	0.575	0.089
4	0.675	0.188

distortion parameters (proportion and intensity level of core attributes plus proportion and intensity level of secondary attributes included in the individual description) we manipulated only the proportion of core attributes (P^c) included in the individual description, the three other distortion parameters are kept constant across panels. Thus, the heterogeneity of the four panels is given by the mean value and the dispersion level of P^c (Table 3); the lower the mean value and the higher the dispersion, the more heterogeneous the panel.

Among the four panels, Panel 2 is more homogeneous than Panel 1, whereas Panel 3 and Panel 4 are more heterogeneous than Panel 1. All simulations (one for each panel) are run with Product 1 as pivot product. A CA is run on each generated frequency matrix using XLStat 2013 (Addinsoft, Paris, France). RV coefficients (Robert & Escoufier, 1976) are computed to compare every possible pair of CA spaces on the coordinates of the products including the four axes of the CA space. RV coefficients are obtained using FactoMineR (Lê et al., 2008) in R language (R Development Core Team, 2007).

3.3.2. Results

CA maps derived from the simulated PP with the four panels are presented Fig. 8. To evaluate the stability of PP, we compared the CA spaces using RV coefficients computed over the four dimensions (Table 4). Product configurations on CA spaces are highly correlated; RV coefficients range from 0.925 to 0.984. The product space of Panel 3 seems slightly more different (i.e., lowest RV coefficients) from the product space of the other panels. This panel was constructed with a low P^c mean value and a low P^c standard deviation meaning that all individual descriptions are highly distorted. Product space of Panel 2 is close to the product spaces of Panel 1 and Panel 4 that have higher P^c standard deviations. This could indicate that heterogeneity among panelists is not a major issue for PP.

3.4. Discussion

As for other referential methods such as Polarized Sensory Positioning (PSP), the choice of the reference product (pivot product) is obviously the major issue in this new approach. However, as only one reference is used in PP compared to three in PSP this issue is probably less critical for PP than for PSP. To produce meaningful descriptions, the products chosen as references in PSP have to be widely different (de Saldamando, Delgado, Herencia, Giménez, & Ares, 2013) implying a good knowledge of the product space beforehand. This is not the case for PP and the PP simulations seem to indicate that the choice of the pivot does not impact product description space in a dramatic way. Yet, a reference product has still to be chosen in PP.

In some situations, the choice of the pivot product could be driven by the objectives of the study. It might be the product of the company that run or order the study for benchmarking purpose or the standard product when adapting recipes or processes in R&D projects. In other situations, there is no standard. Based on the idea of category prototype (i.e., a central representation that shares the most properties with the other items of the category), an alternative would be to create a “central product” by blending all products to be described. This alternative would optimize the chances of describing all aspects of every tested product. But of course, this is an option only for liquid, semi-liquid, or powder products that can be easily mixed.

Still another option would be to consider each product in turn as the pivot. This would probably lead to more stable descriptions. But, this alternative could be considered only when a few products are to be described; when the number of products increases, the experimental load becomes too high for sensory analysts as well

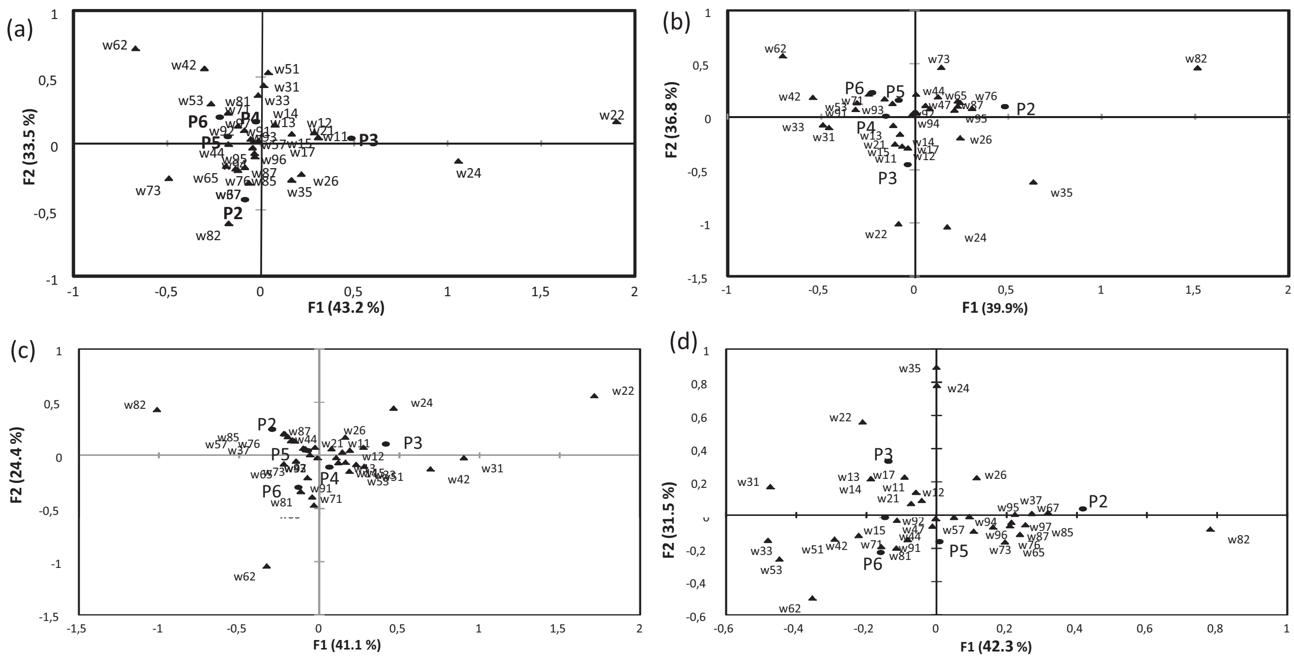


Fig. 8. Projection of the products in the CA map (subspace 1–2) obtained from simulation for four panels. Panels are (a) Panel 1; (b) Panel 2; (c) Panel 3; (d) Panel 4.

Table 4
RV coefficients of CA products spaces across panels.

	Panel 1	Panel 2	Panel 3	Panel 4
Panel 1	–			
Panel 2	0.984	–		
Panel 3	0.937	0.925	–	
Panel 4	0.959	0.986	0.934	–

as participants, unless considering balanced incomplete block designs. This approach would also have the merit to provide experimental data to every product and thus all products appear on the CA map. When the pivot is chosen among the set of products to be described, no experimental data are collected for this product and although products are described in reference to this product, it does not appear on the CA map. To help interpretation, the theoretical position of the pivot can be located on the map by adding a row containing only zeroes to the frequency matrix (before translation). It will give the position of the pivot on the CA map.

In descriptive analysis, as well as in other types of sensory tests, the heterogeneity of the panel is an issue. The conventional profile and associated methods such as QDA or Spectrum cope with heterogeneity by training panelists (Giboreau & Dacremont, 2003). By contrast, fast descriptive methods cope with heterogeneity by including large number of panelists and implementing specific statistical methods (such as GPA, AFM, Statis, etc.). Through PP simulations, we showed that several sets of heterogeneous individual descriptions lead to similar product descriptive spaces. However, in these simulations, the panel size (12 panelists) was relatively low and actually closer to the panel size of conventional profile than the panel size of fast descriptive methods (CATA, PSP, Projective Mapping, etc.). The simulated heterogeneity levels were probably underestimated compared to actual untrained panels performing free description. In the simulated panels, each panelist used no more than 20 percent of personal terms ($P^s = 0.1$ or 0.2), whereas Giboreau et al. (2009) reported about 40% of hapax (word used once by only one participant) in an actual panel of 12 untrained panelists using free vocabulary to describe the touch of 18 materials. Thus, with consumers, the panel size would probably need to be higher than 12 panelists. If the PP is performed by consumers after a hedonic test, the number of panelists is surely large enough. But, when the PP is implemented by itself, the number of panelists could be reduced. In other frequency-based approaches where lists of attributes are provided, the number of participants usually ranges from 50 to 100 (Varela & Ares, 2012) when implemented with consumers. It could be lowered when panelists describe sensory characteristics of products from a list of attributes on which they were trained (Campo et al., 2010). However, the optimal number (i.e., the lowest number, large enough to provide robust description) has not been systematically explored and is still an open question.

4. General discussion

The objective of the present work was to explore the potential of a new frequency-based descriptive method: the Pivot© profile. The experimental part of the work showed that this new approach is promising. Simulations indicated that PP seems robust regarding both the choice of the pivot product and panel heterogeneity. Although, these aspects need to be further confirmed by experimental work, they underline the potential of PP. This new method can be added to the other fast descriptive methods developed these last years (Valentin et al., 2012; Varela & Ares, 2012) to expend the sensory analysts' toolbox.

As already mentioned one major indication for PP is the description of products with experts (enologists, perfumers, etc.) who are used to free description and are often reluctant to use classic sensory evaluation methods that depart too much from their usual practices. PP allows them to express their perception as usual, but provides an experimental framework that helps to collect and interpret data.

PP can potentially be used with consumers to provide fast product descriptions. As other frequency-based approaches such as CATA, Labeled free sorting (Faye et al., 2004) or Ultra Flash Profile, PP provides an approximation of attribute intensities by citation frequencies; the higher the citation frequency, the more intense the attribute. Thus, if fine differences have to be revealed, for example to understand the impact of recipe or process changes, the conventional profile is definitively most appropriate. When the descriptions aim at revealing drivers of liking, the CATA approach might be more appropriate as it is less demanding for consumers, faster to perform with fewer samples to consume, and allows to collect information regarding non sensory aspects such as affects (Ng, Chaya, & Hort, 2013a) or conceptualization (Ng, Chaya, & Hort, 2013b). In other situations, such as understanding representations stored in memory, the Labeled free sorting or Projective mapping tasks are undoubtedly more efficient.

Experimental constraints may also orientate methodological choices. The use of fast descriptive methods (perhaps with the exception of CATA) is very difficult or even impossible to implement when the number of products that can be tested simultaneously is very limited. This is the case for numerous cosmetic products for which there are only two spots of application such as mascara, one on each eye, deodorant, one on each arm pit, or shampoo, one on each scalp-half, etc. The number of products to be compared is also limited for products that change rapidly such as carbonated beverages, ice creams or dishes that cool down rapidly; products containing active substances such as strong alcohols or medicinal products; and products needing a long application before testing such as wearing test for plasters. PP could fill this methodological gap and bring an especially suitable answer. Of course, similarity-based approaches can be implemented by testing every possible pair of products or using balanced incomplete block designs, but this is much more demanding (and often just out of reach) in terms of number of samples per participant or of number of participants compared to PP.

The aforementioned advantages over comparative methods also hold for CATA. And obviously, PP is more difficult to implement in terms of vocabulary analysis: lemmatization (suppressing plurals, verb conjugations, etc.), semantic grouping (based on word meaning), and elimination of the least frequently cited terms, which takes long to perform and is subject to transcoder's mediation (Symoneaux, Galmarini, & Mehinagic, 2012). The CATA method overcomes the issue of vocabulary analysis by providing participants with a list of attributes. But on the other hand, participants' responses are limited to the list and, with this respects, PP results may be richer.

In CATA, the setting up of the list is also a delicate step. The relevance and the communicative value of the words included in the list are decisive for the quality of product descriptions and even the order of the words in the list could impact the outcome (Ares & Jaeger, 2013). One special aspect to consider when setting up the attribute list, is how to refer to dimensional properties. Descriptive characteristics can be either dimensional qualities or identifying characteristics (Katz, 1925/1989). Identifying characteristics (such as sandy, lemon, floral, etc.) refer to an object and are relatively easy to manipulate with CATA. As the feature is either absent or present, participants check the term whenever the feature is detected whatever the intensity. However, for dimensional qualities (such as hardness, moistness, temperature, etc.), a level of intensity has to be indicated by either a degree modifier (slightly, very much, etc.) or using different words that refer to meaningful levels of intensity such as soft, firm and hard for hardness (Normand, 2002). Thus, when describing one sample, one has to set a criterion to decide whether the hardness level of the texture is hard enough to be called "hard" rather than "firm" or "firm" rather than "soft". But decision criteria are known to vary from one participant to another and even for the same participant according to the experimental design. The PP approach overcomes this problem. Whatever way participants refer to the dimension (firm or hard) they still agree on the ranking (the hardness level is higher for the tested than for the pivot product, or inversely). Providing that the experimenters are able to identify all the words referring to the same dimensional quality, all judgments involving these words can be cumulated. This would lead potentially to a more sensitive measurement and easier data interpretations.

5. Conclusion

Pivot© profile is a new fast descriptive method that expands the sensory analysts' toolbox. PP seems especially suited for product description with professionals used to free description and often reluctant to use classical sensory analysis methods. It is also useful for specific products (cosmetic, hot/frozen products, medicinal products, etc.) that are difficult to test simultaneously as each tested product is compared to the pivot product one at a time. The experimental as well as the simulation results show the promises of this approach. More work is needed however to fully grasp the methodological issues of this method.

Appendix A. Modeling details

A1. Individual description of products

The individual descriptions are derived from a prototypical description by distortion according to a set of rules.

A1.1. Prototypical descriptions of products

The prototypical description is given by the list of core attributes followed by their intensity level in brackets which is set at one by definition. Core attributes are adjacent cells in the matrix representing the lexicon (Fig. 3). The six prototypical descriptions considered in the simulations are given Table A1. They are the basis to generate individual description of products according to the construction rules.

A1.2. Construction rules

For each product, the individual description is generated from the prototypical description following four steps: (1) selection of a subset of core attributes, (2) determination of the intensity associated to core attributes, (3) selection of other words adjacent to the core attributes (called secondary attributes), and (4) determination of the intensity associated to secondary attributes. Thus,

Table A1
Prototypical description of the six products considered for simulation.

Product	Description
P1	$w_{22}[1]$, $w_{33}[1]$, $w_{42}[1]$, $w_{44}[1]$, $w_{53}[1]$, $w_{62}[1]$, $w_{73}[1]$, $w_{82}[1]$
P2	$w_{65}[1]$, $w_{67}[1]$, $w_{76}[1]$, $w_{85}[1]$, $w_{87}[1]$, $w_{95}[1]$, $w_{96}[1]$, $w_{97}[1]$
P3	$w_{11}[1]$, $w_{15}[1]$, $w_{17}[1]$, $w_{21}[1]$, $w_{24}[1]$, $w_{31}[1]$, $w_{33}[1]$, $w_{42}[1]$, $w_{53}[1]$, $w_{26}[1]$, $w_{35}[1]$, $w_{44}[1]$
P4	$w_{14}[1]$, $w_{51}[1]$, $w_{57}[1]$, $w_{62}[1]$, $w_{94}[1]$, $w_{33}[1]$, $w_{53}[1]$, $w_{44}[1]$
P5	$w_{65}[1]$, $w_{76}[1]$, $w_{85}[1]$, $w_{87}[1]$, $w_{96}[1]$, $w_{31}[1]$, $w_{42}[1]$, $w_{53}[1]$
P6	$w_{71}[1]$, $w_{81}[1]$, $w_{82}[1]$, $w_{91}[1]$, $w_{62}[1]$, $w_{44}[1]$, $w_{42}[1]$, $w_{53}[1]$

w_{ij} referring to "words" of the lexicon presented Fig. 3, represent core attributes used to describe products. Attribute intensity is given in brackets; set to 1 by convention in prototypical descriptions.

for each panelist, the level of distortion is determined by four parameters:

- P^c: the proportion of core attributes included in the description; range 0–1.
- I^c: the intensity level associated to the core attributes; range 0–1.
- P^s: the proportion of secondary attributes included in the description; range 0–1.
- I^s: the intensity level associated to the secondary attributes; range 0–1.

The four steps are formally implemented using the following notations:

N: number of words in the lexicon.

Np: number of attributes in the prototypical description (core attributes).

Nc: number of core attributes to be included in the individual description.

Ns: number of secondary attributes to be included in the individual description.

$I^c{}_i$: intensity associated to the ith core attribute of the description, $i \in [0, \text{Nc}]$.

$I^s{}_j$: intensity associated to the jth secondary attribute of the description, $j \in [1, \text{Ns}]$.

Step 1: Selection of the sub-set of core attributes to be included in the individual description

First, the number of core attributes to be selected is computed as:

$$\text{Nc} = \text{Integer }(\text{Np} \times P^c) + 1 \tag{1}$$

Then, the Nc core attributes to be included are randomly selected among the Np core attributes of the prototypical description.

Step 2: Determination of the intensity associated to the core attributes

Intensities of core attributes must satisfy the constraint:

$$\sum_i I_i^c = \text{Np} \times P^c \times I^c \tag{2}$$

so that the sum of the intensities associated to the core attributes is constant for any generated description. To reach this constraint (Nc − 1) randomly selected core attributes are set at I^c. The intensity of the remaining attribute is then computed as:

$$(\text{Np} \times P^c \times I^c) - [I^c \times (\text{Nc} - 1)] \tag{3}$$

Step 3: Selection of the secondary attributes included in the individual description

The number of secondary attributes to be included is computed as:

$$\text{Ns} = \text{Integer }[(N - \text{Np}) \times P^s] + 1 \tag{4}$$

The Ns secondary attributes are randomly selected among all the words adjacent to the core attributes of the prototypical description.

Step 4: Determination of the intensity associated to the secondary attributes

Similarly to core attributes, the intensities of the secondary attributes must satisfy the constraint:

$$\sum_j I_j^s = \text{Ns} \times P^s \times I^s \tag{5}$$

so that the sum of the intensities associated to the secondary attributes is constant for any generated description. To reach this constraint, the intensity of (Ns − 1) attributes randomly selected among the Ns secondary attributes, is set at I^s. The intensity of the remaining attribute is then computed as:

$$[(N - \text{Np}) \times P^s \times I^s] - [I^s \times (\text{Ns} - 1)] \tag{6}$$

A1.3. Panel characteristics

A panel includes 12 panelists varying in terms of distortion to account for inter-individual differences among panelists. The distortion level of each panelist is determined by the four parameters: P^c (proportion of core attributes included in the individual description), I^c (intensity level associated to the core attributes), P^s (proportion of secondary attributes included in the individual description), I^s (intensity level associated to the secondary attributes). It increases with decreasing values of P^c and I^c and increasing values of P^s and I^s. P^c values range from 0.5 to 0.9, half of the panelists has a I^c value set at 0.8 and the other half at 0.4; two-third of the panel has P^s value set at 0.1 and one-third at 0.2; I^c value is set at 0.5 for all panelists. As an illustration Table A2 shows the characteristics of Panel 1.

A2. Simulations

For each simulation, we considered a panel of 12 panelists and six products. The prototypical descriptions of the six products are kept constant for every simulation.

A2.1. Construction of the individual description for the six products

As an illustration, we present the construction of the description of Product 1 by the panelists of Panel 1. The prototypical description of Product 1 (Table A1) is: $w_{22}[1]$, $w_{33}[1]$, $w_{42}[1]$, $w_{44}[1]$, $w_{53}[1]$, $w_{62}[1]$, $w_{73}[1]$, $w_{82}[1]$. Thus, Np, the number of core attributes is 8.

To generate the individual description of Product 1 by Panelist 1, we applied the four distortion criteria (Table A2) of this panelist: $P^c = 0.7$; $I^c = 0.8$; $P^s = 0.1$; $I^s = 0.5$ to the four construction steps described Section A1.3.

Step 1: Selection of the sub-set of core attributes to be included in the description

The number of core attributes to be kept is computed as: Nc = Integer (8 × 0.7) + 1 = 6, and thus, six attributes are randomly selected from the eight core attributes (w_{22}, w_{33}, w_{42}, w_{44}, w_{62}, w_{73}).

Step 2: Determination of the intensity associated to the core attributes

The intensity level of all attributes is set to $I^c = 0.8$ excepting for one randomly selected attribute for which the intensity is computed according to Eq. (3) as: $(8 \times 0.7 \times 0.8) - [0.8 \times (6 - 1)] = 4.48 - 4 = 0.48$ and thus, the intensities of the core attributes are: $w_{22}[0.8]$, $w_{33}[0.8]$, $w_{42}[0.8]$, $w_{44}[0.8]$, $w_{62}[0.8]$, $w_{73}[0.48]$.

Table A2
Distortion parameters of panelists included in Panel 1.

Panelists	P^c	I^c	P^s	I^s
1	0.7	0.8	0.1	0.5
2	0.9	0.8	0.1	0.5
3	0.7	0.4	0.1	0.5
4	0.9	0.4	0.1	0.5
5	0.6	0.8	0.1	0.5
6	0.8	0.8	0.1	0.5
7	0.6	0.4	0.1	0.5
8	0.8	0.4	0.1	0.5
9	0.5	0.8	0.2	0.5
10	0.7	0.8	0.2	0.5
11	0.5	0.4	0.2	0.5
12	0.7	0.4	0.2	0.5

Table A3
Descriptions of Product 1 by Panel 1.

Panelists	w_{22}	w_{33}	w_{42}	w_{44}	w_{53}	w_{62}	w_{73}	w_{82}	w_{35}	w_{71}	w_{81}	w_{24}	w_{31}	w_{51}
1	0.8	0.8	0.8	0.8	0	0.8	0.48	0	0	0	0	0.5	0.5	0.45
2	0.8	0.8	0.8	0.8	0.8	0.8	0.16	0.8	0	0	0	0.5	0.5	0.45
3	0.4	0.4	0.4	0.4	0	0.4	0.24	0	0	0	0	0.5	0.5	0.45
4	0.4	0.4	0.4	0.4	0.4	0.4	0.08	0.4	0	0	0	0.5	0.5	0.45
5	0.8	0.8	0	0	0	0.8	0.64	0.8	0	0	0	0.5	0.5	0.45
6	0.8	0.8	0.8	0	0.8	0.8	0.32	0.8	0	0	0	0.5	0.5	0.45
7	0.4	0.4	0	0	0	0.4	0.32	0.4	0	0	0	0.5	0.5	0.45
8	0.4	0.4	0.4	0	0.4	0.4	0.16	0.4	0	0	0	0.5	0.5	0.45
9	0.8	0.8	0	0	0	0.8	0	0.8	0.5	0.5	0.5	0.5	0.5	0.4
10	0.8	0.8	0.8	0.8	0	0.8	0.48	0	0.5	0.5	0.5	0.5	0.5	0.4
11	0.4	0.4	0	0	0	0.4	0	0.4	0.5	0.5	0.5	0.5	0.5	0.4
12	0.4	0.4	0.4	0.4	0	0.4	0.24	0	0.5	0.5	0.5	0.5	0.5	0.4

Step 3: Selection of the secondary attributes included in the description

The number of secondary attributes to be included in the description is computed according to Eq. (4) as Ns = Integer $[(37 - 8) \times 0.1] + 1 = 3$ and thus, three secondary attributes (w_{24}, w_{31}, w_{51}) are randomly selected from the 12 words adjacent to the core attributes of the prototypical description (w_{11}, w_{12}, w_{21}, w_{24}, w_{31}, w_{51}, w_{35}, w_{71}, w_{81}, w_{91}, w_{92}, w_{93}).

Step 4: Determination of the intensity associated to the secondary attributes

The intensity level of secondary attributes is set to $I^s = 0.5$ excepting for one randomly selected attribute for which the intensity is computed according to Eq. (6) as: $[(37–8) \times 0.1 \times 0.5] - [0.5 \times (3 - 1)] = 1.45 - 1 = 0.45$ and thus, the intensities of the secondary attributes are set to w_{24}[0.5], w_{31}[0.5], w_{51}[0.45]. To sum up, the description of Product 1 by Panelist 1 is: w_{22}[0.8], w_{33}[0.8], w_{42}[0.8], w_{44}[0.8], w_{62}[0.8], w_{73}[0.48], w_{24}[0.5], w_{31}[0.5], w_{51}[0.45]. The same procedure is used to construct the individual descriptions of every panelist, leading for Panel 1 to the individual descriptions given in Table A3.

The process is repeated for every product.

A2.2. Simulation of PP outcome

In PP, the panelists' task is to compare one product to the pivot product. This is done for each tested product successively. We simulated this task at the individual level by comparing individual descriptions of the tested product to the description of the pivot product. For attributes included in descriptions of both the tested and the pivot products, the panelist judgment is considered as "less intense" whenever the intensity of the tested product is lower than the intensity of the pivot product on this attribute (symmetrically, the panelist judgment is "more intense" whenever the intensity of the tested product is higher than the intensity of the pivot product). For attributes included in the description of the tested product but not in the description of the pivot product, the panelist's judgment is considered as "more intense", as we consider that the intensity of this attribute in the pivot product is 0.

The outcomes of the comparison between individual descriptions of pivot and tested products are recorded in an intermediate $k \times 2N$ frequency matrix, with k: the number of tested products, and N the number of words in the lexicon. The $2N$ columns are denoted $\mathbf{f}w_{ij}+$ and $\mathbf{f}w_{ij}-$. The column $\mathbf{f}w_{ij}+$ indicates the number of panelists for which the test product was more intense than the pivot product on attribute w_{ij} (and symmetrically, column $\mathbf{f}w_{ij-}$ $-$ indicates the number of panelists for which the test product was less intense than the pivot product). From this intermediate frequency matrix, a $k \times N$ matrix is computed that shows the relative frequencies obtained by subtracting the number of "less intense" outcomes from the number of "more intense" outcomes for each attribute: $(\mathbf{f}_{wij}+) - (\mathbf{f}_{wij}-)$. Last, a translation is performed to get only positive values in the final frequency matrix by adding the absolute value of the lowest value of the whole matrix to each cell. The final frequency matrix is analyzed by Correspondence Analysis.

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