

1 **Exploring consumer product profiling techniques and their linkage to a Quantitative**
2 **Descriptive Analysis**

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18
19 **Abstract**

20 Consumer's voice is crucial for new product development. One way to capture it is to ask
21 consumers to describe products and to quantify their perception of this description. In this
22 context four profiling methods; Sorting, Projective Mapping, Flash Profile and Repertory Grid
23 Method (RGM) were explored among target consumers of hot beverages in two European
24 countries (UK and France) with the assumption that meaningful sensory descriptors can be
25 generated and quantified, and that product maps can ultimately be drawn. A Quantitative
26 Descriptive Analysis was also performed with a trained panel and its outcomes were used as
27 a basis for comparison. Results showed that consumers were able to describe and quantify
28 product differences, that their perception was similar on a cross-country level, that trained
29 panel maps translated well consumers' description, and that Flash Profiling and RGM were
30 more suitable for such a task as they generate a rich vocabulary and more accurate maps.
31 However, when describing complex attributes as mouthfeel or afterfeel, the consumers'
32 description was not enough detailed or not consensual.

33
34 **Keywords:** New Product Development, Sorting, Projective Mapping, Flash Profile, Repertory
35 Grid, Quantitative Descriptive Analysis, Sensory, Consumers.

36

37 1. Introduction

38 Sensory evaluation can be seen as a link between Research and Development, with a focus
39 made on technical aspects of food, and Consumer and Marketing Research, with a focus on
40 consumers' behaviour and psychology (Dijksterhuis, 1997). They measure the reaction to
41 stimuli resulting from the use or consumption of a product through analytical and/or affective
42 tests. Traditionally, analytical tests (discriminative and descriptive) are performed with
43 trained panels whereas affective tests are run with consumers (Stone and Sidel, 1993).

44 QDA^(R) method is based on the principle of a panellist's ability to verbalize perceptions of a
45 product in a reliable manner; panellists are screened and trained in attribute recognition and
46 scaling, they use a common and agreed sensory language, and products are scored on
47 repeated trials to obtain a complete, quantitative description (ASTM, 1992). Describing the
48 sensory characteristics of products has been an integral part of the food and beverage
49 industry since long ago. Information obtained from the description of the sensory
50 characteristics of food and beverages enable companies to make more informed business
51 decisions (Stone and Siedel, 1993). Sensory profiling of a product can guide product
52 development teams on what to change to match the consumer's desired sensory profile, to
53 get closer to a benchmark, to detect detailed differences created by a change of an
54 ingredient, etc.

55 The hypothesis that consumers are able to accurately describe products is more and more
56 managed within the sensory science community. A first step in the development of effective
57 techniques was the exploration of some methods like Repertory Grid Method, or the
58 emergence of new ones as Sorting, Projective Mapping (known also as Napping®) or Flash
59 Profiling. Several researches have already used these methods and focused on their
60 validation with panels who have received different levels of training (Faye et al., 2004;
61 Nestrud and Lawless, 2008; Perrin et al., 2008) but not much was done to assess the
62 comparative applicability of all this methods with the use of naïve consumers panels.

63 The sorting task aims to detect meaningful sensory characteristics within pairs of samples
64 that explain similarities and dissimilarities within the investigated sample set. The method
65 was applied to various sorts of products: breakfast cereals (Cartier et al., 2006), plastic
66 pieces (Faye et al., 2004) and beers (Chollet and Valentin, 2001) to mention a few. It
67 consists of sorting products into groups according to their similarities. The method has the
68 advantage that it can be applied to a large sample set but it often needs to be completed by
69 a verbalization task in order to describe the groups formed and to explain the dimensions of
70 the resulting perceptual map (Popper and Heymann, 1996).

71 Projective Mapping, and its variant Napping®, are profiling methods that were developed
72 (Risvik et al., 1994, Pagès, 2005) in order to collect an Euclidian configuration for each
73 assessor in a single sensory session. Samples, simultaneously presented, are positioned by
74 each assessor on a tablecloth or a blank paper according to the differences/similarities
75 (sensory distances) present between them in such a way that the smaller the distance
76 separating two samples, the more similar they are (Perrin et al., 2008). The positioning
77 criteria and their importance are chosen on an individual basis by each assessor, which
78 makes Projective Mapping a flexible and spontaneous procedure.

79 Data are entered as position coordinates (x and y, with an origin that can be placed
80 anywhere (Perrin et al., 2008) and the judgments of the assessors are equally taken into
81 account. However, the number of samples presented should be limited to sets of 10-20
82 samples in order to limit fatigue or adaptation (Schifferstein, 1996). Similarly to Sorting,
83 Projective Mapping does not describe the product itself and needs to be completed with
84 either instrumental or sensory data (Pagès, 2005) or with a verbalization task to better
85 understand the perceptual dimensions.

86 Flash profiling was defined by Siefferman (2000, 2002) as a combination of Free Choice
87 Profiling with a comparative evaluation of the product set. It is a flexible method meant to
88 position products rapidly according to their sensory attributes. It proved to be as satisfactory
89 as conventional profiling when products are very different in terms of sensory attributes
90 (Dairou and Sieffermann, 2002). However, when the tested products belong to the same
91 product category or to similar product categories, Flash Profiling appears to be more
92 discriminating than conventional profiling (Delarue and Sieffermann, 2004).

93 The repertory grid method (RGM) is based on the theory of personal construct psychology
94 developed (Kelly, 1955). It associates meanings with products as bipolar constructs and
95 results in a broad picture of how decisions are taken (Russell and Cox, 2003). For an
96 example an assessor can be given three drinks and he/she may say that two of them are
97 fruit-based while the third one is a dairy drink. "fruit-based drink" is a construct in this context.
98 In general, RGM is conducted in two sessions. The first one is dedicated to the attribute
99 generation where products are presented in triads to the assessors who are asked to
100 differentiate 2 samples from a third within each triad and explain why. The second session is
101 a rating session in which samples are given scores for each of the elicited attributes.
102 Assessors can also be asked to define a scale to quantify each perceived construct
103 (attribute). This way, each assessor builds his/her own attributes and scales which are then
104 used as in Free-Choice Profiling (FCP), in order to obtain a configuration of N objects in K
105 dimensions (Williams and Langron, 1984).

106 The objectives of this study were, (a) to prove whether naïve consumers are able to describe
107 hot beverages and generate relevant attributes by four descriptive methods: sorting,
108 projective mapping, Flash Profiling and Repertory Grid Method; (b) to compare the
109 consumers' description of the same sample set in 2 countries of the EU: the United Kingdom
110 and France, looking at the influence of the language in the description; (c) to critically
111 compare the applicability of the four methods and to correlate the outcomes to a trained
112 consumer panel description via quantitative descriptive analysis.

113

114 **2. Material and Methods**

115

116 **2.1 Sample set**

117 A sample set of 8 hot beverages (seven samples plus one of them repeated), was used to
118 perform the four descriptive methods. In the quantitative description by the trained panel
119 (QDA), all of the 7 samples were evaluated by duplicate. The 7 products were selected in
120 order to cover a wide flavour space, with distinctive sensory properties.

121

122 **2.2. Sample preparation and serving designs**

123 The drinks were served warm (at 70-75 °C) immediately after preparation, in 3-digit coded
124 paper cups. Tasting evaluation was performed in individual booths, under white light and at
125 room temperature. Samples for Sorting, Projective Mapping and Flash Profiling were
126 delivered to consumers in the three cases all at once, to be compared. In session 1 of the
127 Repertory Grid Method (RGM) samples were presented to consumers in 3 triads were the
128 samples were rotated, to avoid position and carry over effects, using a presentation design
129 following a MOLS design (multiple orthogonal Latin squares). For the second session of the
130 RGM and the quantitative descriptive analysis, samples were presented sequentially,
131 following a Latin square design.

132

133 **2.3. Panels**

134 **2.3.1. Trained panel**

135 A panel of 11 trained assessors tasted and described the same sample set as the
136 consumers did. Panellists were trained in the assessment of the category of products,
137 varying in tasting experience from 1 to 15 years.

138 **2.3.2. Consumer panels**

139 Sorting, Napping, Flash Profiling and Repertory Grid methods were tested using a different
140 panel of 24 naïve consumers each, who were recruited by a recruiting agency according to

141 the following screening criteria: frequent consumers of the category in study (hot beverages),
142 not rejecters of milk or sugar, ages between 18 and 65, 50% males, 50% females.

143 At the end of each tasting session, the consumers were asked to fill in a feedback form and
144 answer questions related to the understanding, ease and time-effectiveness of each profiling
145 method they used.

146

147 **2.4. Profiling methods**

148 **2.4.1. QDA**

149 Samples were completely rotated and 2 repetitions were completed. The evaluation
150 proceeded in 3 sessions of 2 hours each:

151 Session 1 – Training: Samples were presented to the panellists in pairs. A list of 42
152 attributes corresponding to the hot beverage product category was used for the assessment.

153 In this step the panellists rated the pair of samples perceived intensities on 150 mm closed-
154 end unstructured scales. This task informed about whether an attribute was perceived by the
155 panellists, and allowed assessing the degree of consensus in the ratings. If discrepancies in
156 attributes or ratings were detected, an open discussion was prompted, in order to arrive to a
157 consensus. Attributes selected for the data collection step were the ones utilized by at least
158 half of the panel (23 attributes in total).

159 Sessions 2 & 3 – Sensory evaluation & repetition: Samples were presented to the panellists
160 in a sequential monadic way following a Latin Square Design generated by Fizz (FIZZ 2.40B,
161 Biosystems, France). They entered their intensity ratings by logging in a FIZZ QDA session
162 built for 7 products and including the 23 selected attributes, using closed-end unstructured
163 150mm scales displayed on computer screens. *Session 3*: was a repetition of session 2 in
164 order to check the performance of the panel as well as the reproducibility and attribute
165 interactions as used by the panellists.

166 **2.4.2.Sorting**

167 Sorting was performed in one session of approximately 40 minutes, including briefing. The 8
168 samples were given all at once and consumers were then asked to observe, smell and taste
169 them and then to group them according to their similarities, the number of groups formed
170 should be no less than 2 and no greater than 7. Similar procedure was applied by Cartier et
171 al. (2006), Faye et al. (2004), Chollet and Valentin (2001), and Giboreau et al. (2001). Once
172 the sorting was performed, the consumers were asked to describe each of the groups they
173 formed by giving their grouping criteria using sensory descriptors (Cartier et al., 2006). They
174 reported their answers on individual ballots.

175 **2.4.3. Projective mapping**

176 The exercise was completed in one session of about 40 minutes, including briefing. Samples
177 were presented simultaneously and the consumers were asked to observe them, smell them
178 and taste them and then to position them according to individual criteria on a blank A3 sheet
179 according to perceived similarities and/or differences in such a way that: (a) two samples are
180 close to each other if they're similar; (b) two samples are far from each other if they are
181 different (Pagès, 2005).

182 After positioning the cups on the A3 sheet, the consumers were asked to describe the
183 samples and/or groups of samples (Perrin et al., 2008). The description comments were
184 written on the A3 sheet next to each cup and/or group of cups. The cups were left on the
185 sheets and their (x,y) coordinates were measured by the test leader and entered on a Excel
186 sheet.

187 **2.4.4. Flash Profile**

188 FP was carried out in one session of one hour, including briefing. Coded samples were
189 presented simultaneously and the consumers were asked to observe, smell and taste them
190 in order to generate descriptors (on an individual basis). The next step was to rank all
191 samples from "least" to "most" according to each attribute (Delarue and Sieffermann, 2004;
192 Dairou and Sieffermann, 2002).

193 The flash Profiling task was performed by a consumer panel in Banbury, UK and another
194 one in Paris, France.

195 **2.4.5. Repertory Grid Method**

196 RGM was conducted in two sessions of an overall duration of 2,5h including a 20 minute
197 break, and a briefing part.

198 **Session 1: Attribute generation:** Samples were presented in triads following a balanced
199 rotation in such a way that all samples appear at the same frequency. Each consumer was
200 given 3 trays in order to allow the tasting of the whole the sample set. For each tray, the
201 consumer was asked to pick the odd sample out and to explain in which way it is different
202 from the two other samples and also in what way these two samples are similar (Russel and
203 Cox, 2003; Monteleone et al., 1997; Thomson and McEwan., 1988, Gonzales-Thomas and
204 Costell, 2006). The consumers entered their answers on individual ballots and had a break
205 of 20 minutes after finishing the attribute generation for the 3 trays. During this break, the
206 test leader entered the generated attributes on intensity rating ballot sheets to be used in the
207 second session. Synonyms as well as attributes related to liking were omitted.

208 **Session 2: Intensity rating:** Samples were presented in a sequential monadic series. The
209 task consisted in rating the perceived intensity of the attributes generated in the first session
210 for each sample, using 150mm closed-end, unstructured scales with the extremes "Not at
211 all" and "Extremely". Thus, each assessor had his/her own list of attributes.

212

213 **2.5. Data analyses**

214 Depending on the profiling method used in this project, the attribute elicitation can be
215 combined or not with a rating and/or ranking task and thus the type of generated data is
216 either qualitative, quantitative or both. This implies a cautious selection of the most adapted
217 multivariate analysis. For both Sorting and Projective Mapping, frequency of mention scores
218 of synonyms and repeated sensory attributes were combined and considered as one
219 variable in the data analysis (i.e.: dull, mild, bland would be entered as dull/mild/bland with a
220 frequency of mention that is the sum of the frequencies of each word).

221 Table 1 explains the choice of the data analysis method for each profiling technique used to
222 obtain a sensory map.

223 In the case of the PCA, GPA and MFA methods, the number of relevant dimensions was
224 selected by looking at the scree plots; the number of factors to be kept corresponding to the
225 first turning point found on the curve. For MDS analysis the Shepard diagram was used to
226 observe any ruptures in the ordination of the distances which helped choosing the number of
227 dimensions.

228 Apart from these methods, and for all the profiling techniques, Hierarchical Cluster Analysis
229 was applied in order to group samples as per their complete sensory profiles. More detailed
230 description of the methods of choice for each technique can be found below.

231 The following software programs were used for data processing: Senpaq 4.2 (QIstatistics,
232 UK) for checking trained panel performance, Fizz Acquisition and Fizz calculations (Fizz
233 2.40B, Biosystemes, France) for the trained panel data collection and analysis, and XLSTAT
234 2008.1.03 (Addingsoft, USA) for the rest of the data analysis.

235 **2.5.1. Sorting**

236 Individual similarity matrices [Products X Products] were built for each consumer by entering
237 the number of times at which each pair of samples was sorted in the same group.

238 The sum of the similarity matrices, of all consumers, resulted in an overall similarity matrix
239 which was then transformed into a dissimilarity matrix by subtracting the matrix data from the
240 total number of consumers. The overall dissimilarity matrix was processed by XlStat
241 functions (Describing Data and Multi-Dimensional Scaling (MDS)) to deliver a proximity
242 matrix and further on a configuration of the sample set in two dimensions, dim1 and dim2. As
243 the defined measure of dissimilarity between samples can not be considered as numerical
244 data, a non-metric; Ordinal 1 model was applied. In order to explain these two dimensions, a
245 matrix (Products x Attributes) was built by listing all the attributes generated by the
246 consumers and by summing their frequencies of mention for each product. Spearman
247 correlation was then determined between the attribute frequencies of mention and the

248 product positions in dim1 and dim2. This way it was possible to plot the attributes over the
249 product configuration obtained from the MDS calculations.

250

251 **2.5.2. Projective Mapping**

252 Multiple Factor Analysis (MFA) was performed with XIStat on data obtained from the
253 positioning of the products on the A3 sheets as well as the attributes each consumer
254 generated to describe the products. The product coordinates were measure in centimetres
255 and attributes listed together with their frequencies of mention across the consumer panel,
256 resulting in three tables: x, y, attributes (Figure 1).

257 **2.5.3. Flash Profiling and RGM**

258 Individual matrices for each consumer (Products x Attributes) were built in order to enter
259 product rankings (from FP) or intensity ratings (from RGM). A GPA was then performed on
260 the 24 matrices in order to obtain the product and attribute configurations.

261 **2.5.4. Quantitative Descriptive Analysis**

262 Summary statistics involving the calculation of means, standard deviation and ranges were
263 carried out aiming to get an overview of the complete data set.

264 Panel performance was evaluated with the use of Senpaq 4.2 (QIstatistics, UK) package,
265 performing ANOVA with a fixed model, checking discriminatory ability, reproducibility and
266 scale usage of each panellist, as well as each panellist's contribution to interaction.

267 Analysis of variance (ANOVA) with the use of a mixed model (assessors as random effect)
268 was performed for testing product set significant differences. Multiple comparisons were
269 performed with Tukey's test at 5%. A principal component analysis (PCA), based on the
270 Pearson's correlation matrix, was conducted on the means of the attributes presenting
271 significant differences. PCA allows the profile data to be summarised in a smaller number of
272 dimensions than the total attributes in the profile (principal components). Each component
273 represents a certain percentage of the total information or variability of the original profile
274 data. Samples and sensory attributes can be projected onto these components and
275 summary plots can be produced. PCA is a statistical tool that helps to summarise and
276 therefore, communicates better the results from descriptive panel profiling.

277 **2.5.5. Other Statistical Analyses**

278 Hierarchical Clustering Analysis (HCA) was performed in order to highlight product clusters
279 as perceived by the trained panel and by the consumer panels. Method details were:
280 dissimilarity: Euclidean distance, agglomeration method: Ward's method, automatic
281 truncation.

282 Consumer cross-method comparisons were based on visual similarities of the product
283 positioning on the profiling maps, their description, the identification of the internal repetition,
284 as well as the number of sensory attributes generated.

285 Maps were correlated with the trained panel map using a MFA in such a way that mean
286 scores from the trained panel were considered as an additional data set to consumers'
287 individual data

288

289 **3. Results and discussion**

290

291 **3.1. Quantitative Descriptive Analysis – trained assessors**

292 Taking into consideration the ANOVA results obtained through the PCA analysis of the
293 descriptive data conducted by the trained panel, revealed a clear discrimination of the
294 sample set following 18 attributes related to aftertaste, flavour and mouthfeel. The first 2
295 dimensions explained over 84% of the variability, describing the most important sensory
296 attributes of this sample set, main perceptual directions are represented in the map.
297 Hierarchical Clustering Analysis (HCA) revealed 3 groups of products (Figure 2).

298

299 **3.2. Sorting – naïve consumers**

300 When performing a MDS, the difference is measured through the stress, several variations
301 of which have been proposed: Raw, Normalized, Kruskal's 1&2. In this work, the best fit
302 delivered by the MDS was obtained at a Kruskal's stress (1) $K=0.089$. However the panel's
303 performance was not satisfactory as the internal repetition was not mapped in a relevant way
304 (P3 and P3 Rep are far from each other). After manually overlaying the product and attribute
305 maps, it was observed that the products were well described by the attributes (figure 3). For
306 instance: P1 was described as weak in taste, smell and aroma, mild and with a vanilla
307 flavour, P2 was described as dark and rich in colour with a strong taste, P3 was described
308 as creamy, sweet and not bitter and P4 as being bitter, sharp and intense. However, P1
309 occupied an intermediate position between P2 (a bitter and strong sample) and P4 (an
310 intense and unsweetened sample) while it was expected to be placed far from both samples
311 according to the QDA results.

312 The low performance of the sorting task could be explained by the fact that the sensory
313 assessment as described by this method tends to group the products following one sensory
314 dimension only: consumers sorted the samples following one main criterion (appearance,
315 smell or taste) even if many grouping options could exist for each product; that could mean
316 that the final configuration might not contain enough sensory attributes for a

317 multidimensional map to be relevantly built. Adding a verbalization task to sorting allowed a
318 better understanding of the obtained results. The generated attributes were in fact consistent
319 with each sample's sensory profile. For instance, even if P1 (a bland, milky and sweet
320 sample) was placed between P2 (intense, bitter and sweet) and P4 (unsweetened, intense),
321 it was described as 'milky', 'bold', 'tasteless'.

322 Similar findings were obtained for breakfast cereals by Cartier et al. (2006) who compared
323 sorting with an untrained panel to QDA. Moreover and when repeated, sorting results
324 (product mapping and description) showed to be consistent over time (Cartier et al., 2006;
325 Lawless and Glatter, 1990). Faye et al. (2004) on the other hand found that sorting of leather
326 pieces with consumers gave results which were consistent with the trained panel's results in
327 terms of product positioning and description. This can be explained by the complexity of the
328 sensory profile of the investigated product and the level of the training.

329 The success of a sorting task with consumers would then very much rely on the differences
330 within the sample set. If they are big, and involving multivariate perceptions (appearance,
331 aroma, flavour, manual and oral texture, aftertaste), consumers would be indeed able to
332 discriminate between them, and most probably would use similar attributes to describe those
333 differences, resulting in a good consensus map of the samples. In the present study, most
334 of the differences were in flavour and aftertaste, being all liquid products; these facts added
335 up to the uni-dimensionality of the sorting task, explain the low performance of it as a
336 mapping procedure. The hypothesis is that, in a more complex sample, consumers would
337 naturally tend to use multiple sensory attributes and different dimensions in the sorting task
338 (texture, flavour, aroma), in contrast to a rather plain food as a hot beverage is. More
339 research would be needed to validate this hypothesis.

340

341 **3.3. Projective Mapping – naïf consumers**

342 Figure 4 shows the product positioning coming from the MFA of the projective mapping data.
343 The map obtained was quite comparable to the QDA map, though the first two dimensions
344 only explained 45% of the variability. Nonetheless, and apart from P1 which was placed on
345 its own following the 'Milky/Creamy' vector, P2, P3, P3 Rep and P7 occupied the same
346 space. These products were identified as being part of the same cluster in the QDA results
347 of the trained panel. This means that the consumers were also able to identify these
348 samples as similar to each other and different from the other products even if they could not
349 perceive well the underlying differences present within the cluster (figure 4 shows small
350 distances between these samples). However, even if the sample P3 and the internal
351 repetition are closer to each other with the Projective Mapping results than they are with the
352 Sorting results, the internal repetition did not seem to be obvious to the consumers. Apart

353 from that, the discrimination of the samples was lower than expected; samples were not
354 separated as per the clusters identified with the trained assessors.
355 Attribute wise, the basic attribute directions describing the sample set were identified and
356 were aligned with the QDA descriptors; P2, P3/P3 Rep and P7 are driven by sweetness in
357 general but also by coffee intensity and bitterness which they shared with samples P4, P5,
358 P6, and P1 by milkiness/creaminess. The relevant positioning of the products showed that
359 PM performed better than Sorting and this can be explained by the fact that PM is a bi-
360 dimensional procedure where samples are placed on a surface following the perceived
361 similarities/dissimilarities between them. Such task could be appropriate to highlight big
362 differences but was not precise enough in pointing out more accurate differences between
363 samples in the present study. Perrin et al. (2008) applied a similar approach where
364 Napping® was combined to Free Choice Profiling and performed with both a trained panel
365 and a panel made of wine professionals. The study was however more focused on the
366 validation of Napping as a relevant profiling method and was not performed with naive
367 consumers as it is the case here. The results obtained by Perrin et al. showed in fact that
368 Napping gave a good product positioning with a rough description which was not as accurate
369 as the QDA profile's description. Nestrud and Lawless (2008) however, stated that Projective
370 Mapping would perform better than sorting as it provides richer data sets per assessor in
371 addition to the fact that product positions on the 'nappe' can inform about their similarities.

372

373 **3.4. Flash Profile – naïf consumers**

374 **3.4.1 UK Panel**

375 The relative configuration of the samples obtained from the FP procedure is very similar to
376 the one obtained from the QDA. As shown in figure 5, the consumers were able to perceive
377 the differences and similarities between the samples with the first two dimensions explaining
378 more than 82% of the variability. This is made even clearer when looking into the main
379 attribute directions highlighted in the map, where it can be observed that 'bitterness' and
380 'colour intensity/coffee intensity' described P2, P4, P5 and P6. These attributes were
381 negatively correlated with 'sweetness', 'smooth/creamy' and 'bland/weak' which described
382 P1, P3/P3 Rep and P7. The 'Creamy' attribute seemed however not to be well understood or
383 agreed on by the consumers as it covered a wide space (shaded area in figure 5). It can be
384 explained by the fact that consumers do not have the same understanding of 'creamy' (and
385 related words e.g.: cream, creaminess) and that creaminess is an integrated attribute
386 associated to flavour, texture and pleasantness of food products (Tournier et al., 2007).

387 The product clustering obtained with the HCA (ellipses shown in figure 5) is the same as the
388 one obtained from the QDA results. The panel's performance was highlighted by the fact that

389 samples P3 and P3 Rep were positioned close to each other and both belonged to the same
390 cluster.

391 These findings are in agreement with those from Dairou and Sieffermann (2002) who
392 conducted a study comparing conventional profiling and flash profiling performed on 14 jams
393 using respectively a trained panel and a panel made of students with a relevant experience
394 in sensory methodology. The results obtained revealed that both methods produced similar
395 results in terms of positioning and description of the jams, with flash profiling being faster but
396 less self-explanatory than conventional profiling. Another study comparing the evaluation of
397 dairy products (strawberry yogurts and apricot-flavoured fresh cheese) with Flash Profile and
398 a conventional profiling (as QDA or Spectrum), both with a trained panel, showed that flash
399 profiling was more discriminating than conventional profiling but that it was less adapted to
400 the description of the investigated product category (Delarue and Sieffermann, 2004).
401 Sieffermann and col. successfully proved that FP is a valid method for a quick product
402 profiling with the use of trained assessors but did not explore the validity of its use with naive
403 consumers as it is the case here; the present study gives a further step in proving the
404 applicability of such technique as a profiling method .

405 **3.4.2. French Panel**

406 The French panel was also able to position the samples in a relevant way in comparison with
407 the QDA product plot (figure 2), as well as to represent the expected differences and
408 similarities present within the sample set. The first two dimensions explained about 84% of
409 the variability (figure 6).

410 With regards to the attributes (figure 6), the main directions were similar to those observed
411 for the outcomes of the QDA with the trained panel. The HCA also revealed the same
412 product clustering as in the QDA results. The French panel was consistent in describing the
413 differences/similarities within the sample set (P3 and P3 Rep came out close to each other
414 on the GPA product configuration).

415 When comparing the FP results from the UK and French panels, it appears that both
416 delivered similar product positioning, clustering and description (attribute directions), with the
417 first two dimensions explaining more than 82% of the variability. Moreover, and as long as
418 the 'creamy' attribute is concerned, it seems that the French panel, just like the UK panel,
419 used this attribute to describe different perceptions. A translation of the French terms is
420 given in table 2.

421 Apart from the main attribute directions shown in figure 6, the attribute correlation as given
422 by the GPA also reveals some interesting well correlated attributes such as 'viande' (meat) ,

423 'odeur céréales' (cereal smell), 'gout aspartame' (aspartame flavour) and 'acidité'
424 (sourness).

425 Consumers from France and the UK are quite different in consumption habits and
426 preferences for this category of products. The fact of finding very similar outcomes in both
427 cases shows that Flash Profiling could be used regardless the liking patterns of the
428 consumers, providing they are not rejecters of the category. Another potential application
429 coming from the results of the present study is that FP could be applied in different
430 languages to get more insight about consumer relevant attributes in the target country, and
431 to compare to the attributes used by the trained panel.

432

433 **3.5. Repertory Grid Method**

434 The GPA results from the RGM data sets shown in figure 7 revealed a relevant relative
435 positioning of the samples in the perceptual space, and also a pertinent description of the
436 perceived differences; 83% of the variability was explained by the first two dimensions only.
437 Both configurations (products and attributes) were consistent with the QDA results. The HCA
438 product clustering results were identical to those obtained for QDA as well as for Flash
439 Profiling and showed that the sample set could be discriminated into three clusters.

440 The comments made about the 'creamy' attribute as mentioned by the consumers in the FP
441 task, can also be made for the RGM results. 'Creamy' is obviously a complex attribute that
442 probably covers creamy mouthfeel, creamy flavour, creamy smell and creamy appearance.
443 In addition to the main attribute directions, the attribute map obtained from the GPA revealed
444 the following most correlated attributes: 'biscuity' scent, nut taste, cocoa taste, caramel, dry,
445 sour, palatable, smooth, artificial, tangy taste and coffee strength.

446 RGM has already been performed with consumers but with the objective to understand
447 consumers' perception of a product rather than comparing consumers' profiling with a
448 trained panel's profiling and the aim of obtaining a product perceptual map (Russel and Cox,
449 2004, applied to the description of meat products; Hersleth et al., 2005, applied to bread).
450 Nonetheless, the results of these studies showed an alignment between the product
451 positioning and description given by the consumers and those revealed by the trained panel.

452

453 **3.6. Generated vocabulary**

454 The four investigated product profiling methods proved to generate a fair amount of sensory
455 relevant attributes (Table 3). As presented in the mapping results, there was consensus in
456 the use of these attributes by the consumer panels and the core sensory attributes of the
457 sample set matched the trained panel's description. Table 3 gives the main results through
458 the four profiling methods. It can be observed that even if Sorting and Projective Mapping

459 were not very well suited for mapping objectives in this study, they proved to be an
460 acceptable way of vocabulary development; they generated a high amount of attributes,
461 although only 12% and 14% of these attributes were respectively relevant, after taking out
462 non sensory words and grouping synonyms . These findings are very important as a way to
463 validate the trained panel vocabulary, ensuring that what is analytically measured reflects
464 relevant perceptions for consumers. It also proves that the methods tested in the present
465 work could be used to generate vocabulary related to the product category in different target
466 countries, to study which words are used by consumers to speak about the different aspects
467 of a product sensory design.

468 It is worth mentioning that for all methods, hedonic and non-sensory attributes such as
469 'natural appearance', 'bad flavour' or 'nice smell' were not included in the data analysis.
470 Others such as 'right sugar balance' or 'correct coffee balance' were considered respectively
471 as 'sugar' and 'coffee', whereas attributes like 'not bitter' or 'no coffee flavour' were used as
472 such.

473 **3.6.1 Sorting**

474 The top 20 most mentioned generated attributes are listed in table 4. They count for 20% of
475 the generated vocabulary with over 53% of the frequencies of mention.

476 **3.6.2. Projective Mapping**

477 The most frequently mentioned sensory attributes generated are listed in table 5 and it can
478 be seen that this table is quite similar to the one obtained with the sorting task. However,
479 about 50% of the attributes generated by Projective Mapping were mentioned only once
480 across the panel.

481 Projective mapping also generated 32 non-sensory words among which we can find some
482 interesting ones such as: 'forgettable', 'has heart and soul', 'pleasant' and 'little to
483 distinguish'.

484 **3.6.3. Flash Profile**

485 The vocabularies generated by the UK and French panels were quite similar and (table 6),
486 'sweet', 'bitter', 'colour', and coffee taste/strength were in the top 5 most mentioned words for
487 both panels. Moreover, the top 20 most frequently mentioned attributes by both panels
488 accounted for 73% and 75% of the attributes generated by the UK and the French panels
489 respectively.

490 Table 6 also highlights the common attributes between the British and French panels (in
491 bold). These account for more than 60% of the attributes generated if we exclude the
492 synonyms (e.g. darkness=colour dark, smell = strength of smell, etc.). The UK panel also
493 generated 3 non-sensory words: choice, 'nice horrible' and 'perfect recipe' whereas the
494 French panel did not generate any.

495 **3.6.4. RGM**

496 The top 20 most frequently generated attributes with RGM are very comparable to those
497 generated by FP (table 7). They represent about 40% of the generated attributes with 80%
498 of the frequencies of mention. 'Sweet' was mentioned by nearly every consumer and
499 'colour', strength of taste', 'bitter' and by more than half of the panel.

500 The vocabulary generated by RGM and considered for the GPA analysis did not contain any
501 non-sensory descriptors. This is most probably due to the fact that the vocabulary was
502 elicited thanks to straightforward questions in the 1st session of RGM (task question : "Pick
503 the odd sample out within the triad, explain in what way it is different from the two other
504 samples and in what way these two are similar). Additionally, the first step in vocabulary
505 generation for RGM (triadic elicitation) is screened down by the panel leader for allowing the
506 rating stage of the sensory descriptors in the second step.

507

508 **3.7. Correlation of consumer and trained panel results**

509 FP and RGM were identified as the best suited methods in terms of product consumer
510 profiling, accomplishing both mapping and description objectives. Their perceptual maps
511 were subsequently correlated with the maps obtained from the QDA using MFA as a way to
512 better understand the correlation between consumers' product attributes and the attributes
513 from the trained panel. MFA was performed considering the mean scores from the trained
514 panel as an additional data set to the consumers' individual data, this way the structure of
515 the product configuration was maintained as per the consumer's description. MFA makes it
516 possible to analyze several tables of variables simultaneously, and to obtain charts that
517 allow studying the relationship between the observations, the variables and tables
518 graphically. The originality of this method is that it allows visualizing in a two or three
519 dimensional space, the tables, the variables, the principal axes of the analyses, and the
520 individuals. In addition, the impact of the other tables on an observation can be studied by
521 simultaneously visualizing the observation described by the all the variables and the
522 projected observations described by the variables of only one table (Escofier and Pagès,
523 1984).

524 The correlation map via MFA showed that the two first dimensions explained up to 65% of
525 the variability for FP, with a high correlation ($R_v=0.91$) and 60% for RGM ($R_v=0.88$).
526 Moreover, the descriptors generated by the consumers in both cases reflected well those
527 used by the trained panel. For instance, the 'Sweetness' perceptual direction as described
528 by the trained panel, is positively correlated with descriptors such as 'sweet', 'sweetened'
529 and sugar' which were generated by the consumers, the 'Bitterness' direction as described

530 by the trained panel explains consumer words such as ‘strong taste’, ‘bitter’ or ‘intense’.
531 These results confirm the suitability of these two techniques as a means of obtaining a
532 consumer relevant product mapping as well as their ability to generate a list of words to
533 describe the samples in “consumers’ language”.

534 Nevertheless, as mentioned before, the consumers’ perception of ‘creamy/creaminess’ was
535 not well correlated to the trained panel assessment. Moreover, the QDA results revealed a
536 more detailed description of the samples in some aspects, not described in depth by the
537 consumer panels, particularly on mouthfeel perception and aftertaste/afterfeel. These
538 findings suggest that there is a limit in the quality of information that can be obtained via
539 consumers’ description. The use of MFA to correlate data sets from different profiling
540 methods was particularly useful in this study as it provided a graphical idea of how the data
541 sets related, i.e. whether the attributes were explained in the same way by both panels being
542 compared (trained panel and consumer panel), and what the discrepancies were (see figure
543 8 as an example of the correlation of RGM and QDA results). This allowed the observation
544 that the “creamy” perception was not quite well described by consumers.

545

546 **3.8. Practical considerations and applications**

547 A straightforward application of the evaluated consumer profiling techniques is when there
548 are time constraints, when a trained panel is not available or a new category of products is
549 being tested in which the internal panel is not well trained.

550 Nevertheless, it has to be pointed out that the objective of this study was not to find new
551 methods to replace descriptive techniques with trained panels but to further understand how
552 methods as QDA relate to consumer perception.

553 Moreover, trained panel descriptive measurements perform better in various cases: when
554 there is a need to compare samples in different moments in time and also when comparing
555 different sample sets with few samples in common, as although not absolute, when the
556 panel is well calibrated and maintained, trained panel measurements are stable both in time
557 and within a certain perceptual space. Another example is when small differences have to be
558 described; or as aforementioned, when the difference lays in more complex perceptions like
559 mouthfeel and afterfeel, in those cases a panel with intensive training is still needed, and
560 could be a crucial source of information in product development applications.

561 The other objective of this research was to critically compare the effectiveness and
562 application of different profiling methods, for the first time done with multiple techniques, on
563 the same sample set, and with different panels of naïf consumers, allowing a thorough
564 comparison. The results showed that Sorting, Projective Mapping, Flash Profiling and
565 Repertory Grid Method, all could be applied as a means of generating vocabulary in hot

566 beverage samples; however, FP and RGM present the advantage of being also well suited
567 as descriptive techniques for a quantitative product mapping. However, one limitation has to
568 be highlighted for FP; being a comparative method, the number of samples that can be
569 assessed by FP is limited (and would depend on the category), while in RGM and QDA, as
570 samples are presented in a monadic sequence, there is no potential limitation regarding
571 maximum number of samples.

572 FP and RGM data can be used with confidence to correlate with sensory data from a trained
573 panel, or also with physical or chemistry data. Furthermore, the correlation of FP or RGM
574 and QDA would be a strong validation of the descriptive panel glossary. The feasibility of
575 quantifying consumer description in a relevant way via FP or RGM also opens the door of
576 the exploration of consumers' vocabulary with a more statistical validity (contrary to
577 traditional qualitative exploration methods as focus groups). As an example, some useful
578 questions could be answered: "which consumer attributes discriminate better between two
579 samples"?, "what attributes are more relevant to the target consumers"?, "do consumers
580 have the same understanding of a particular attribute?", "what different words describe the
581 same sensory stimuli for a naive consumer?", resulting in an interesting guidance to product
582 developers. This could also be a way of identifying important attributes to consumers with
583 the objective of having them into account in further quantitative affective testing of the
584 category (central location test or home use test), particularly when the target country has a
585 different language than the one managed by the research team.

586

587 **4. Conclusions**

588 The results obtained in this study proved that consumers were able to generate relevant
589 attributes and to quantify differences between hot beverage samples.

590 Sorting and Projective Mapping performed poorly in terms of product discrimination and
591 repeatability, but both are quick and user-friendly techniques that could be used when a
592 broad and rough description is needed.

593 Flash Profiling and RGM were accurate in terms of mapping and clustering; these methods
594 also produced a relevant and rich description. Consumers' measurement by FP and RGM
595 (understood as product positioning and description) was very comparable to the
596 measurement performed by the trained panel, however, when describing mouthfeel (e.g.
597 creaminess) the consumers' description was not enough detailed or consensual.

598 The good performance of FP and RGM with consumers makes them reliable methods which
599 can be recommended for obtaining a description when a quick profiling is needed or when
600 the panel of trained assessors is not available or not trained in that particular product.

601 Sorting and Projective Mapping on the other hand can be used as easy and quick product
602 profiling procedures when an accurate profiling is not needed and when a rough description
603 is sufficient.

604 All the methods studied could be used as direct feedback from target consumers, as good
605 vocabulary development tools; however FP and RGM being more accurate at profiling can
606 be used also to correlate to data from a trained panel and even to physical and chemistry
607 data.

608 In this work, trained panel attributes reflected well consumers' perception of the product
609 category in study, serving as a validation of the trained panel glossary. In general, trained
610 panel descriptive measurements still would perform better in some applications and can not
611 be substituted, particularly when complex attributes are involved, as in this case mouthfeel
612 and afterfeel, or small differences need to be characterized.

613 The profiling techniques researched here are seen as complementary to the information
614 given by a trained panel, being very powerful tools to obtain direct feedback from
615 consumers. Next steps would be to study "how far can these methods go", i.e. are they
616 applicable to most product categories? In which cases are they better suited or not suited at
617 all?

618

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623

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695 **FIGURE CAPTIONS**

696

697 Figure 1: Schematic exemplifying view of how projective mapping data were treated: x_1 and
698 y_1 are the coordinates of P1 for consumer 1, x_2 and y_2 are the coordinates of P1 for
699 consumer 2, etc. Attributes were recorded with the frequency of mention per product;
700 “sweet” was mentioned 6 times for P1, etc.

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702 Figure 2: PCA product map from QDA assessment (attributes not shown, main attribute
703 directions are represented in the map). Ellipses highlighting product clusters as revealed by
704 HCA

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706 Figure 3 : Product configuration obtained by MDS from the Sorting task (Overlaying of
707 Spearman correlation of attributes)

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709 Figure 4: Product configuration obtained by MFA from the Projective Mapping task. Vectors
710 show the most correlated attribute directions

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712 Figure 5: Product configuration obtained by GPA from the Flash Profiling with the UK panel.
713 Vectors show the most correlated attribute directions. Shaded area shows the “creamy
714 perceptual space”. Ellipses showing clusters from HCA

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716 Figure 6: Product configuration obtained by GPA from the Flash Profiling with the French
717 panel. Vectors show the most correlated attribute directions. Shaded area shows the
718 “creamy perceptual space”. Ellipses showing clusters from HCA

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720 Figure 7: Product configuration obtained by GPA from the RGM task. Vectors show the most
721 correlated attribute directions. Shaded area between two vectors shows the “creamy
722 perceptual space”. Ellipses showing clusters from HCA

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724 Figure 8: Correlation of RGM and QDA results obtained by MFA. Vectors show the most
725 correlated attribute directions generated by consumers. Shaded area between two vectors
726 shows the “creamy perceptual space”. Names of QDA attributes are not shown.

727

728 TABLES

729

730 **Table 1: Product profiling methods versus adapted multivariate analysis technique**

Method	Data analysis	Reason
Sorting	MDS	- Maps the pattern of similarities or dissimilarities perceived among a set of products/objects by computing the frequencies of sorting which each pair of products in the same group
Napping®/ Projective Mapping	MFA	- Analyzes several tables of variables which differ in number and nature from one another - Within a table, the variables must be of the same nature (quantitative or qualitative) - Integrates different tables of variables describing the same observations
Flash Profiling Repertory Grid Method	GPA	- Reduces the scale usage effects - Delivers a consensus configuration (consensus in the use of attributes come from the usage of the same/similar attribute by different panellists) - Allows to compare the proximity between the terms that are used by different assessors to describe products
Quantitative Descriptive Analysis	PCA	- Delivers a consensus configuration (attributes are also consensual between panellists) - Allows to compare the proximity between the terms that are used by different assessors to describe products

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739 **Table 2: Translation of French discriminating attributes**

French attributes	English translation
Amertume	Bitterness
Puissance gout	Taste strength
Puissance arome	Aroma strength
Intensité de la couleur	Colour intensity
Sucré	Sweet
Gout lacté	Milky taste
Crémeux	Creamy
Saveur creme	Creamy flavour
Gout caramel	Caramel taste
Acidité/saveur acide	Sour/sour flavour
Odeur céréales	Cereal smell
Café grillé	Roasted coffee
Viande	Meat
Gout aspartame	Aspartame taste
Onctuosité	Creamy mouthfeel

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754 **Table 3: Cross-method and Cross-country key figures for generated vocabulary**

	Sorting	PM	FP UK	FP France	RGM
Number of attributes generated	233	247	136	118	162
Average per consumer	8.6	9.2	5.3	6.2	6.3
Number of attributes excluding repetitions and non-sensory words	27	34	54	45	49

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777 **Table 4: Top 20 most frequently mentioned attributes with Sorting**

Attributes	Frequency of mention	Attributes	Frequency of mention
sugar/sweet	14	not sweet	4
bitter	13	watery	4
strong	12	bland	3
cream	9	medium coffee	3
dark	9	milk	3
weak	9	no coffee taste	3
mild	8	pale	3
smooth	7	slightly bitter	3
rich	5	strong smell	3
mellow	4	strong taste	3

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796 **Table 5: Top 20 most frequently mentioned attributes with Napping®**

Attributes	Frequency of mention	Attributes	Frequency of mention
sweet	18	mellow	4
bitter	13	milk	4
creamy	13	pale colour	4
strong	12	coffee taste	3
rich	8	mild	3
weak	8	mild flavour	3
dark	7	no flavour	3
bland	6	not bitter	3
no coffee taste	5	not sweet	3
watery	5	nutty taste	3
aftertaste	4	smooth	3
dark colour	4		

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816 **Table 6: Top 20 (16 for the French) most frequently mentioned attributes with FP for**
 817 **the British and French panels. In bold are highlighted the common attributes between**
 818 **the two panels.**

UK Panel		French Panel		
Attributes	Frequency of mention	Attributes	English translation	Frequency of mention
strength/strong/strongest	17	saveur sucrée	Sweet taste	18
sweetest	14	amargor/amer	Bitter	13
bitter	11	couleur (intensité)	Colour intensity	12
colour/appearance	10	gout lacté/arome lait	Milky taste/milk flavour	10
smooth/smoothness	7	gout café	Coffee taste	5
creaminess	5	intensité d'odeur	Smell intensity	5
aroma	4	odeur café	Coffee smell	4
darkness	4	acidité	Acid/sour	3
richness	4	arome café	Coffee aroma	3
smell	4	couleur marron	Brown colour	3
after taste	3	gout (intensité globale)	Taste (overall intensity)	3
taste	3	aqueux	Watery	2
bland	2	arome (intensité globale)	Aroma (overall intensity)	2
colour dark	2	café	Coffee	2
depth / strength of coffee	2	corps	Body	2
miliness	2	onctuosité	Smoothness	2
nuttiness	2			
smell intensity/intensity	2			
smooth flavour/taste	2			
strength of aroma/smell	2			

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821 **Table 7: Top 20 most frequently mentioned attributes with RGM**

Attributes	Frequency of mention	Attributes	Frequency of mention
sweet	24	flavour/flavoursome	3
colour	19	mild/bland	3
strength of taste	19	coffee smell	2
bitter	14	dry	2
creaminess	9	mellow	2
smooth	6	palatable	2
weak	6	rich	2
coffee taste	4	smell	2
milkiness	4	strength of smell	2
strength of aroma	4	thick	2

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