

1 **Projective mapping based on choice or preference: an affective approach to**
2 **projective mapping.**

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14 **Abstract**

15 This work explores a new affective approach to projective mapping, based on consumers'
16 choices or preferences. Two sessions, one week apart, were performed with the same
17 consumers, using whole bread as a case study. Overall liking ratings (OL) were gathered
18 in blind conditions and samples were also profiled by a trained panel using generic
19 descriptive analysis. Three projective mapping tests were performed in different
20 scenarios. Consumers' categorization and product descriptions were explored when
21 consumers based their positioning on the products' similarities and differences (analytical
22 approach, "classic napping") both in blind and informed conditions, and when consumers
23 were focusing on their preference or choice (affective approach). The affective approach
24 to projective mapping successfully revealed consumers' drivers of liking and choice from
25 a holistic perspective, where consumers summarized their main drivers for categorizing
26 products as they would do when choosing in real life situations, based on their
27 preferences.

28

29 **Keywords:** projective mapping; napping; affective; consumers; drivers; preference;
30 choice.

31 **1. Introduction**

32 Projective mapping (also known as Napping®) followed by a descriptive step has been
33 extensively used **with consumers** in the last years as an alternative tool for the description
34 of products and packs. It is considered a holistic approach to product **profiling, closer** to
35 what happens in a choice event when compared to classic descriptive or attribute-based
36 techniques (Varela & Ares, 2012; Valentin et al., 2012). Built on the perception of
37 similarities and differences, it encourages the generation of a global representation of the
38 products, which is usually hindered when consumers are directly asked about multiple
39 particular attributes. Holistic methods enable to identify the main attributes **that account**
40 for the differences **among** the samples without forcing consumers to focus on specific
41 characteristics (Ares & Varela, 2012). In addition, projective methods **make it possible to**
42 **capture** more spontaneous responses than other, more directive, techniques (Guerrero
43 et al., 2010). The projective mapping (PM) task can involve the perception of similarities
44 and differences from an intrinsic (sensory) **perspective, from an** extrinsic (pack, labelling,
45 etc.) perspective, or **from** both (Carrillo, Varela, & Fiszman, 2012a), generally considering
46 product objective characteristics for categorization rather than liking as the main
47 parameter. **Despite this**, consumers often use hedonics or benefit-related terms together
48 with the product and pack descriptive characteristics. **This can be used to relate** product
49 characteristics to marketable features and consumer preferences (Ares & Varela, 2012)
50 **and is an** approach **that** has been applied **successfully** to explore sensory and non-
51 sensory stimuli, such as the influence of packaging information – **e.g.** nutritional and
52 health claims – on consumer perception (Carrillo et al., 2012a; Carrillo, Varela, &
53 Fiszman, 2012b; Miraballes et al., 2014; Varela et al., 2014).

54 When optimizing food products, the general practice has been to ask consumers about
55 liking; the sensory properties would be characterized in parallel by a trained panel, in a
56 preference mapping type of exercise (van Kleef et al. 2006). However, trained assessors
57 may describe the product differently, so sensory characterization based on consumers'
58 direct input **may** have greater external validity (Ares & Varela, 2012). In this sense, overall

59 liking (OL) has been gathered jointly with PM data in some studies in order to draw
60 conclusions on drivers of liking (Ares et al, 2010; Torri et al., 2013) and to better
61 understand the changes in hedonic response in different mapping scenarios (Carrillo et
62 al., 2012b). In a study by Ares et al. (2011), after doing a PM with real samples of
63 powdered orange juice consumers were asked about their ideal product to be mapped.
64 The results were similar to those of external preference mapping. Withers et al. (2014)
65 have used taxonomic sorting, a holistic method also based on sample categorization, to
66 generate diagnostic sensory data directly from target consumers by external preference
67 mapping. Generally, hedonic descriptions or OL have been considered as supplementary
68 variables in PM data.

69 From a different perspective, King, Cliff & Hall (1998) compared PM to a “structured PM”
70 to map snack bars, where they used labeled axes in the PM space: the x-axis was defined
71 as “liking” (low - high) and the y-axis as “usage” (treat - meal replacement). They found
72 the proposed method less discriminating than PM, but only 24 consumers participated in
73 this study. To our knowledge, there have been no other approaches to PM from an
74 affective perspective, with liking or preference explicitly driving sample categorization.

75 Consumers in affective tests act in an integrative fashion, basing themselves on global
76 sensory and non-sensory stimulation from the product – in contrast to the analytical
77 testing frame of mind in descriptive testing (Lawless & Heymann; 2010; Jaeger, 2006).
78 More concretely, since consumers are integrated and organized wholes, as highlighted
79 by Maslow (1954), in real buying and eating situations they take a certain number of
80 attributes (sensory and non-sensory) into account when performing food choices or
81 declaring their preference (Asioli et al., 2017). Thus, consumers would cognitively focus
82 on products differently when describing as opposed to stating their preference or choice.
83 With this background, it is of great interest to study how consumers approach the PM
84 task when preference or choice is used as a criterion.

85 The objective of this study was to explore a new affective approach to projective mapping,
86 with bread as case study, basing product categorization on consumers’ choice or

87 preference, and to compare it to the classic preference mapping approach. This
88 approach might provide information that is more realistic for product developers and
89 marketers during the **product development process and market launch**.

90

91 **2. Materials and methods**

92 **2.1 Samples**

93 Eight commercial wholegrain, pan-loaf breads were used in the study, bought in
94 supermarkets **in the region immediately** south of Oslo (Norway). Products differed in
95 terms of brands, prices, mix of grains used and percentage of wholegrain (Table 1).

96

97 **2.2 Descriptive Analysis with a trained panel**

98 A trained panel of nine assessors at Nofima Mat (**Ås**, Norway) performed a sensory
99 descriptive analysis according to a **quantitative descriptive analysis inspired by QDA®**
100 **with modifications, as described by Lawless and Heymann (2010) as generic descriptive**
101 **analysis**. The assessors were tested, selected and trained according to ISO standards
102 (ISO, 1993) and the sensory laboratory used followed the ISO standards (ISO, 1988).
103 **Nofima's panel is a highly trained and very stable panel; the assessors are solely hired**
104 **as tasters, with a part-time job; some of them have more than 20 years' experience. The**
105 **panel performance is assessed frequently, and checked for every project. The specific**
106 **attribute list for the bread was developed in a one hour pre-trial session using two**
107 **extreme bread samples. After a pre-trial session, the attributes and definitions were**
108 **agreed upon by the assessors: they were all able to discriminate among samples,**
109 **exhibited repeatability, and reached agreement with other members of the group.** The
110 assessors agreed upon 25 attributes describing the bread samples: odour intensity, hue,
111 colour intensity, whiteness, pore size (crumb), amount of seeds/fibres (crust), roughness,
112 elasticity, strength, crumbling, cohesiveness (using the finger), acidic taste, sweetness,
113 saltiness, bitterness, yeast flavour, grain flavour, nut/seed flavour, roasted flavour, rancid
114 flavour, hardness, juiciness, roughness/coarseness, chewiness and stickiness. All

115 attributes were evaluated on unstructured line scales with labelled endpoints going from
116 “no intensity” to “high intensity”. In a pre-test session, the assessors were calibrated on
117 samples that were considered the most different on the selected attributes typical for the
118 breads to be tested. Samples were served in transparent Ziploc® bags labelled with
119 three-digit numbers. Tap water was available for palate cleansing. Two replicates were
120 performed for each bread sample. All samples and replicates were served in **randomized**
121 order following a balanced block experimental design.

122

123 **2.3 Consumer tests**

124 Two sessions, one week apart, were held with the same group of participants and the
125 same eight samples at Nofima Mat (Ås, Norway). In the first session, consumers
126 performed two “classic” PM tests: blind PM (tasting blind samples) and informed PM
127 (tasting together with the pack). In the second session, consumers first rated blind overall
128 liking **followed by** a PM task based on choice or preference in informed conditions (tasting
129 together with the pack). In both sessions, new samples with new codes were delivered
130 for the two tests; consumers had a **minimum of 15 minutes’** break between tests.

131 **2.3.1 Consumers’ sample**

132 The consumers included in the study (n=50) were recruited from Nofima’s consumer
133 database **and** were frequent consumers of wholemeal bread (more than twice per week).
134 The participants were between 34 and 64 years old (**43 years on** average). Each session
135 lasted around 30 min (Figure 1).

136 **2.3.2 Session 1 – Classic PM, blind and informed**

137 All participants were instructed in the use of the PM technique with a descriptive step.
138 The basics of the technique were explained to the participants through an example
139 employing geometric shapes with different colours and patterns, without any **reference**
140 **to bread**. After the explanation of the technique, the participants received an A2 sheet of
141 paper to allocate the samples. Samples were allocated according to the principle that
142 samples with similar characteristics should be placed close to each other, while different

143 samples should be placed further away. Next, they had to write down all the terms they
144 could think of in connection with each sample, or group of samples, on the sheet, next to
145 the position of the respective samples (technique also known as ultra-flash profiling).

146 **Blind PM**

147 The eight bread samples were presented simultaneously for direct comparison. Each
148 sample was presented in a transparent Ziploc® bag coded with a three-digit number on
149 a sticker. This type of presentation facilitated the location of the samples on the A2 sheet.
150 The participants had to observe, smell and taste the breads, and then place the samples
151 on the A2 sheet. Once they decided on the positioning, they were tasked with writing the
152 codes on the sheet, and write the terms describing the perceived characteristics of the
153 sample or group of samples close to the corresponding code.

154 **Informed PM**

155 The participants simultaneously received the eight bread samples in the same way as in
156 the blind test, but this time each with an accompanying scan of the original front-of-pack
157 (FOP), printed in colour. All scans of the FOP had the same dimensions. The participants
158 performed the test in the same way as the blind test, but this time they had to consider
159 both the information received and the sensory characteristics perceived. As before, they
160 had to position the codes of the samples on the A2 sheet, and write down the descriptive
161 terms.

162 **2.3.3 Session 2 (one week apart) – Blind overall liking rating and informed PM** 163 **based on choice or preference (PM-C)**

164 **Blind overall liking rating**

165 Consumers rated their overall liking using 9-point box hedonic scales. Samples were
166 assessed in blind conditions, in a rotated presentation order, balanced for order and
167 carry-over effects (Wakeling & MacFie, 1995).

168 **Informed PM based on choice or preference (PM-C)**

169 Samples were presented in the same way as in the informed PM (bread samples with an
170 accompanying front-of-pack), but with different codes. The instructions of this test

171 differed from the “classic” PM approach in the way in which consumers had to base their
172 categorization and sample allocation. Instructions were as follows (including underlining
173 and capitals): “Please evaluate the samples and look at the packs and position them on
174 the sheet according to their differences and similarities basing your criteria on what you
175 would choose, thinking about different food occasions. Place them on the sheet in such
176 a way that two samples are close to each other if they’re SIMILAR WITH REGARDS TO
177 YOUR PREFERENCE and two samples are far from each other if they are DIFFERENT
178 WITH REGARDS TO YOUR PREFERENCE.” As in the other two tests, after sample
179 allocation, consumers had to write the codes of the samples on the A2 sheet together
180 with descriptive terms.

181 These instructions were fine-tuned in a pilot test session before the main test (n=10). In
182 the pilot, consumers went through the whole test (classic PMs, liking test, and PM-C).
183 After the pilot trial, the researchers had an open discussion in which the consumers
184 participated for feedback. For example, it was decided to add a phrase in the instructions
185 stressing “*what you would choose, thinking about different food occasions*” to avoid
186 consumers thinking they should just rank the samples from most to least preferred,
187 basing their decision on only one consumption situation. In this way, they would
188 understand that they could for example like two or more products equally, but could
189 decide to consume them on different occasions or for different applications. In addition,
190 pilot consumers suggested the categorization basis could be stressed by using capital
191 letters: “*two samples are close to each other if they’re similar with regards to your*
192 *preference*” (and conversely). Based on the pilot it was also decided to include an
193 example of a very different food category: sweet foods/desserts. They had different
194 desserts, such as fresh fruit, yogurt, a gooey cake, etc. so they better understood the
195 idea that it was possible to give multiple reasons for their choice.

196 **2.3.4 Considerations on the experimental design**

197 In session 1, the blind PM was done first and samples and map were taken away from
198 the consumers when they had finished. The second part of the test was not explained to

199 the consumers in advance; all they knew was that they were not done. After the 15-
200 minute break, we instructed the consumers on how to do the informed PM test. The eight
201 bread samples were different enough to be differentiated by means of direct comparison;
202 however, they were eight (similar) slices of brown bread. It is very unlikely that the
203 consumers remembered where they blindly positioned the eight samples from the blind
204 PM to the informed PM, even if performed on the same day. The main driver for this
205 experimental choice was that we wanted to keep the affective-based tests (Liking rating
206 and PM-C) separated from the analytical approaches (classic PMs).

207

208 **2.4. Data analysis**

209 **2.4.1 Preference mapping (sensory panel and consumer liking data)**

210 An internal preference mapping was built through PLSR using the Consumercheck 1.4.2
211 open software tool. Consumer liking was used as the X matrix. The Y matrix were the
212 sensory scores. Through this analysis, a score plot is obtained that visualizes how the
213 products are related to each other in the space spanned by the first principal components,
214 determined by consumer liking. The correlation loading plot shows how the variables of
215 the X and Y matrices contribute to the common variation for each PC.

216 **2.4.2 Analysis of the consumer test data**

217 Analysis of variance (ANOVA) was performed on consumer overall liking scores
218 considering consumer and sample as sources of variation. Mean ratings were calculated
219 and significant differences were checked using Fisher's LSD test ($p < 0.05$).
220 Agglomerative hierarchical clustering (HCA. Dissimilarity: Euclidean distance;
221 Agglomeration method: Ward's method) was utilized as segmentation procedure in order
222 to highlight groups of consumers with different liking patterns. Furthermore, an internal
223 preference mapping was achieved via PCA (Principal Component Analysis) of a matrix
224 of products x consumers to obtain a multidimensional representation of products and
225 consumers in order to check against the clustering results (Varela, 2014). Analysis of

226 variance (ANOVA) and Fisher's test were also run for the clusters obtained, in the same
227 way as above.

228 PM data in the three scenarios were collected as the X and Y coordinates of the samples
229 on each consumer's individual map. A Multiple Factor Analysis (MFA) was performed
230 considering the X and Y coordinates for the samples on each consumer's individual map
231 as a group of variables (Pagès, 2005). Confidence ellipses were constructed as per
232 Delholm et al. (2012). MFA was also carried out to compare the bread sample positions
233 on the maps generated in the four evaluations. Values of RV coefficient were obtained
234 for the purpose of comparing data from each session. RV ranges between 0 and 1; the
235 closer to one, the greater the similarity between the configurations of the data tables.

236 To study if consumers grouped/mapped the samples differently in the three PM sessions,
237 an MFA was conducted for the three tables for each consumer. Then the variability
238 between the consensus of the three sessions was measured by the similarity index
239 proposed in Tomic et al., 2015. In Tomic et al 2015, the SI was used to measure the
240 variability to the consensus. Here we applied the same index for assessing the variability
241 of each consumer across the different sessions. The similarity index (SI) for individual k
242 in session i is computed as:

243

244
$$SI_{ki} = \frac{\|F_{ki} - F_k\|}{F_k}$$

245 Here $\| \cdot \|$ is the Frobenius norm, F_{ik} is the projected coordinates of consumer k from
246 session i and F_k is the consensus of consumer k across the three sessions ($i=1,2,3$,
247 $k=1,2,\dots,n$). The SI was computed for the consensus with A=2 components, hence there
248 are two columns in F_{ki} and F_k . To measure how much the different consumers were
249 influenced by the instructions, the average of SI over sessions was computed for each
250 consumer. Higher SI values indicate that consumer maps were different in the different
251 sessions, and that consumers were more affected by the instructions. There is no upper

252 limit on SI, but a value > 1 indicates that residuals are larger than the variation between
253 the samples within the consensus. The SI can also be computed for the complete data
254 set in one session to measure the overall agreement of the consensus.

255 All the words provided by the participants in the descriptive step of the PM were analyzed
256 qualitatively and differences were statistically checked, as follows: terms mentioned by
257 at least 5% of the consumers were retained for further analysis (Symoneaux, Galmarini,
258 & Mehinagic, 2012). The terms generated to describe the samples were grouped by
259 consensus among two researchers, considering synonymous and derived words. The
260 frequency table containing the terms was considered as a set of supplementary variables
261 in the MFA of the PM data. The frequency of mentions was determined by counting the
262 number of mentions of the same term in each session. Terms were grouped under three
263 categories: *sensory, hedonics and usage & attitudes*.

264 Global Chi-square was used for testing the homogeneity of the contingency table of the
265 terms generated in the descriptive step of the PM in the three scenarios (Symoneaux et
266 al., 2012). When the initial Chi-square was significant, a chi-square per cell was done
267 within each cell identifying the source of variation of the global Chi-square. This was run
268 both for the individual terms and the three formed categories to compare the three
269 scenarios.

270 The MFA analyses from the PM data were performed with the package FactoMineR
271 (<http://factominer.free.fr/>) in R (version 3.2.2).

272 The chi-square per cell analysis was run with an XL macro as in Symoneaux et al. (2012).

273 The rest of the statistical analyses were run in XLSTAT, 2014, Addinsoft, New York

274

275 **3. Results**

276 It is important to point out that the objective of this methodological research was not to
277 draw conclusions on the products themselves, but on how the different approaches to
278 PM (analytical and affective) influenced the product descriptions and product choice
279 information.

280

281 **3.1. Overall Liking & liking patterns**

282 Overall Liking (OL) significantly varied between bread samples (Table 2), ranging from
283 4.1 to 5.9. Preference responses are usually heterogeneous, and mean scores are not
284 always representative of real preference patterns (MacFie, 2007; Felberg et al. 2010).

285 Preference mapping approaches could be applied to understand consumer preference
286 patterns, **together** with sensory data, to look for underlying dimensions that drive
287 consumer preferences (Varela, 2014). In this first section, hierarchical cluster analysis
288 (HCA) and the sensory description via generic descriptive analysis by the trained panel
289 were combined to understand the liking patterns. Cluster analysis could be seen as “the
290 lowest level of preference mapping” (Mac Fie, 2007).

291 HCA highlighted three clusters, one of them composed of only **five** consumers who
292 rejected all samples (scores 4 and under). **Assuming** they disliked the general category
293 under study, the analysis was continued on the other **two** clusters. Table 2 displays the
294 distinct liking patterns of those two clusters. Although both groups of consumers rejected
295 sample **B8**, liking patterns were clearly different. **B8** (barley, extra-coarse), was
296 described by the trained panel as **having a rather** strange, rancid flavor that **may explain**
297 the general consumer rejection.

298 Cluster 1 **discriminated less** among **samples**. **They** rejected **B8** and did not present
299 significant differences in overall liking among the rest of the samples; they were fairly
300 open to any kind of bread but slightly preferred whiter, more cohesive breads.

301 Consumers in cluster 2 on the other hand, had more defined preferences, favouring dark,
302 rough breads, and rejecting whiter, less coarse varieties. **Samples B1 (wholegrain, half-**
303 **coarse) and B5 were most liked and were described as having an intense odour, bitter,**
304 **with nut/seed and roasted flavour, rough, with large pores, and dark. They were followed**
305 **in liking rating** by **B2** and **B7** (rye, extra-coarse), described as chewy, rough, sweet,
306 roasted, dark and strong. **Consumers in cluster 2** clearly rejected **B3** and **B4** (whiter,

307 cohesive, sticky, crumbling, with yeast taste, grain taste and salty), added to the rejection
308 of B8.

309 These liking patterns could be observed in the internal preference map (Figure 2).

310 In the following sections, the obtained two clusters will be explained by the descriptive
311 data obtained by PM with consumers, to contrast with the interpretation provided by the
312 trained descriptive panel. The conclusions that can be drawn with preference mapping
313 approaches, combining classic descriptive data with overall liking, are limited to the
314 sensory drivers of liking or disliking. The use of projective techniques such as PM permits
315 understanding consumer perception beyond its sensory elements (e.g. attitudes, usage,
316 affective terms), potentially revealing other reasons behind the affective response
317 patterns (Ares et al., 2011; Varela & Ares, 2012).

318

319 **3.2. Classic PM vs the new affective approach for understanding consumers'** 320 **perception**

321 **3.2.1. Perceptual spaces – spatial configurations**

322 ***Comparisons of the four evaluations***

323 Sample configurations in the four tasting instances (descriptive analysis with the trained
324 panel and the three PMs with consumers) were highly correlated, with RV coefficients
325 ranging from 0.86 to 0.97. The generic descriptive analysis by the trained panel
326 presented the lowest RVs with respect to all the PM scenarios, but still good enough
327 (0.86). This can also be appreciated from the superimposed representation of the
328 samples in the multiple factor analyses (Figure 3). For most of the samples, generic
329 descriptive analysis was further away in the perceptual space to the consensus, but
330 retained a similar relative position between samples. These results suggest that
331 consumers may have a similar response regardless of whether they are assessing
332 products blindly or informed, and even when basing the evaluation on their preference
333 rather than on the products' descriptive characters. Moreover, the high correlations with

334 the generic descriptive analysis indicate that the assessments are mostly based on
335 sensory aspects.

336 In the descriptive step of blind PM, consumers generated a total of 75 different terms to
337 describe the sample set, comprising mainly sensory terms (47) but also hedonic terms,
338 and some related to usage and attitudes. In the descriptive step of the informed PM,
339 consumers also generated 75 different terms in total, again including a majority of
340 sensory terms (42) and some hedonic terms, as well as terms related to usage and
341 attitudes. The fact that consumers focused more on sensory cues to describe similarities
342 and differences among the samples rather than on usage or other elements accords with
343 the high correlation obtained with the generic descriptive analysis and both classic PM
344 tests.

345 In the descriptive step of the PM based on choice or preference, consumers generated
346 approximately the same number of different terms in total (78); however, in this scenario
347 the number of sensory terms was significantly lower (28), as highlighted by the chi square
348 per cell analysis, and the description was more focused on the usage and attitudes
349 category of terms (39). This shows that although the positioning of the products in the
350 perceptual space might have been similar, consumers' associations when thinking about
351 their preference or choice for different consumption occasions was different, and
352 primarily driven by usage and the situation rather than by specific sensory cues. It should
353 be noted that the PM-C instructions and dessert example primed consumers to think
354 about usage and situations. Despite this, consumers could have used a similar number
355 of sensory terms, which they did not. In a way, that was the idea behind the new
356 approach: to prime them to be more specific about diverse drivers of their choices, going
357 beyond the sensory experience, while also trying to retain the spontaneity of the
358 projective technique as a basis.

359 **Blind PM**

360 Figure 4 shows the perceptual spaces as described by the two first dimensions of the
361 MFA of the two classic PM in both scenarios (blind and informed). In the blind PM

362 (Figures 4 a1 and a2), the two first dimensions of the MFA display 50% of the variability
363 of the original data. Considering together the samples' configuration (Figure 4 a1) and
364 their description (Figure 4 a2), the breads were grouped mainly based on cereal type
365 (oats, rye, barley, with wholegrain and combinations in the centre of the map), as well as
366 fibre content and perception of healthiness. Consumers perceived the samples described
367 as coarser and with a healthier taste (B7, B5, B1), while they associated more standard
368 or ordinary traits with the softer samples on the other side of the first factor.

369 ***Informed PM***

370 In the informed, classic PM: it is clearly visible from the sample configuration (Figure 4
371 b1) that the information polarized the results obtained for sample B8, which was
372 separated from the rest of the samples in the consensus configuration. Evidently, the
373 unique characteristics of this sample, particularly the "off-flavour" described by some
374 consumers in the blind PM evaluation (Figure 4 a2) – in line with the "rancid" in the
375 generic descriptive analysis – made more sense in consumer minds when knowing more
376 about this bread. They mentioned the base cereal (barley and claims), focused more on
377 describing the bad, off-taste, and mapped it further away from the rest. As B8 spans
378 factor 2 of the MFA, the other samples do not show much variation in this direction. The
379 first factor showed the variation of samples "from rye (B7) to oats (B6, B4)" with the
380 wholegrain and mixes in the middle. However, variations in coarseness and darkness
381 can be identified in this factor. The breads perceived as less coarse, or whiter are located
382 towards the right of the plot. It is interesting to see that the information on the whole grain
383 content did not noticeably affect the perception of coarseness, associated with B7 and
384 B5 (extra coarse), but also with B1 (half coarse).

385 ***PM based on choice or preference PM (PM-C)***

386 Figure 5 displays the perceptual space obtained in the PM-C in informed conditions, as
387 described by the two first dimensions of the MFA. Although the relative positioning of the
388 samples in the spatial configuration was not essentially changed, enhanced
389 discrimination between the products can clearly be observed in this scenario. Samples

390 **B6** and **B4**, both made mainly with oats, were the only ones not discriminated in this
391 tasting instance. In the PM-C, consumers used **overall** more words, and **fewer words**
392 **related** to sensory descriptions. The extra information obtained with this type of PM
393 approach can be appreciated in Figure 5 by interpreting the particular description of each
394 sample (descriptive step), which can also be used to better understand the liking patterns
395 as highlighted by consumers. **For** example, Cluster 2 preferred samples **B1**, **B2**, **B5** and
396 **B7**, described in PM-C as dark, tasty, with good texture, a good/exciting taste, with corn,
397 seeds and taste of seeds, sour, coarse, heavy, satiating, rich in fibre, healthy, sporty, for
398 adults, of a **well-known** brand, **rather** expensive, good for dinner, with soup or cheese,
399 and **that** they would buy them. On the other hand, consumers in Cluster 1 tended to like
400 more chewy breads with **a** smooth surface, without whole seeds, **less** coarse, with oats,
401 less tasty or even bland, good when toasted, a low price, everyday bread, for **packed**
402 **lunches**, easily eaten, for families, for children. Meanwhile, **these** characteristics were
403 rejected by cluster 2. The PM-C also helped to further understand the rejection of **B8** by
404 all consumers. It was described as not attractive, **with a** bad, strange taste, off-flavour
405 and odour, bitter, fluffy and porous and it was perceived as unhealthy; consumers stated
406 they would not buy this kind of bread. This supports the idea of the **different** consumers'
407 description in this case, **driven by** the usage occasions and the situation, and only **a few**
408 important sensory cues.

409 ***Descriptive step***

410 Table 3 shows the list of terms mentioned by consumers in the three PM scenarios
411 together with the Chi Square per cell analysis. The terms included in the analysis were
412 the ones cited **by** at least by **5%** of the consumers **of** one product.

413 With respect to the **sensory terms** generated, even if there was a comparable number
414 of different terms cited in the blind (47) and informed PM (42), the frequencies of citation
415 were in general higher in the blind tasting, as consumers relied mostly on the sensory
416 characters **when** explaining their maps. The terms mentioned most **frequently** in the blind
417 PM (with more than 40 mentions) were: bland, bright colouring, coarse, corn, dry,

418 seeds/taste of seeds. In the informed PM, the sensory terms were fewer in total, but the
419 most frequently mentioned were largely the same; however, juicy and smooth surface
420 also became important terms used to describe the samples in this scenario. In the PM-
421 C, the total number of sensory terms was significantly lower (28), as highlighted by the
422 chi-square per cell analysis, and the terms elicited by consumers with high frequency
423 were fewer. However, the words bland, corn and dry continued to be mentioned more
424 than 40 times, but significantly less frequently than in the blind scenario. However,
425 coarseness was mentioned significantly more frequently, going from 44 mentions in the
426 blind PM to 106 mentions in the affective approach (PM-C); this suggests that
427 coarseness may have been one of the most important drivers of product differentiation
428 when considering choices in this particular sample set.

429 The *hedonic terms* category was the one with fewest distinct terms generated by
430 consumers in the three PMs, and the frequencies were also lower. In general, in the blind
431 PM there were significantly more terms that expressed liking or disliking of some sensory
432 characteristics, such as: exciting appearance, good smell, standard appearance and
433 standard texture; however, the number of mentions was low (25 or less). The hedonic
434 term most mentioned in the three PM was good/exciting taste, but there were no
435 differences between them (86-101 mentions). It is quite interesting how two of the
436 hedonic terms significantly increased in the PM-C. Bad taste and would not
437 buy/eat/uninterested became very important in the affective approach, which suggests
438 that consumers were more prone to express their opinions with regards to disliking when
439 grouping the samples based on what they would actively choose (in a real-life scenario).

440 The category of descriptions on *usage & attitudes* was more heavily influenced by the
441 scenario. The number of different terms generated in total more than doubled in the
442 affective approach to PM (from 15 in blind to 39 in the affective approach), and the
443 frequencies of mention of usage & attitudes terms were significantly higher. The terms
444 generated included: target consumers (for kids, for adults, for family), consumption
445 occasions (for breakfast, lunch, dinner, everyday bread, for packed lunches, for sport),

446 food pairings (for soup, with cheese, with toppings, with jam, versatile), health-related
447 properties (healthy, satiating, weight-reducing), references to the brand (good label,
448 standard label), and to the price (expensive, low price). It is interesting to highlight how
449 the price references were almost non-existent in the classic PM scenarios (both blind
450 and informed), and how the references to healthiness increased significantly, apart from
451 focusing much more on the possibilities of product usage .

452 Chi square per cell was also run on the term by product matrix in each scenario, to being
453 able to highlight the different profiles of each sample (data not shown). As stated above,
454 the main objective of this paper was not to describe the samples; nevertheless the study
455 shows that the terms generated by each individual product in the affective PM highlight
456 the important attributes for each sample in the light of the different preference patterns.
457 For example, B8 was associated significantly more frequently with the terms would not
458 buy, bad taste, weird taste, off-flavour, sour taste and non-informative label. Hence it this
459 explains why the product was rejected by most consumers, highlighting the drivers of
460 disliking. On the contrary, B5, the bread liked by both groups of consumers, was
461 associated more frequently with terms such as with a good/exciting taste, tasty, with good
462 smell and good-tasting crust, and consumers found it good both as bread for packed
463 lunches and sporty. In terms of coarseness, it was significantly associated with this
464 concept, but not significantly different to B7, which was viewed to a significantly greater
465 degree as a dark bread, for adults and highly satiating. This suggests that B5 could be a
466 good option for both clusters within the coarser breads, while B7 was very well-liked by
467 Cluster 2 but within the less liked samples in Cluster 1.

468

469 **3.4. Consumers' individual behaviour in the different PM scenarios**

470 A natural question that might be raised at this point is how different consumers, or groups
471 of consumers, reacted to the change in PM scenario. When comparing how samples
472 were located in the perceptual spaces by both liking clusters in the different tests, they
473 were also very similar; for example, comparing the relation of the perceptual spaces

474 obtained by clusters 1 and 2 in the PM-C, RV was 0.882. Something similar happened
475 when comparing the outcomes for the same cluster throughout scenarios; for instance,
476 Cluster 1 had an RV of 0.828 between PM blind vs. PM-C. These results showed that
477 the maps obtained for the groups with similar liking patterns were quite stable throughout
478 different PM tests. However, that was not necessarily the case when studying
479 consumers' individual behaviour. Some of the consumers changed their maps drastically
480 from one scenario to another, while a few others maintained very stable mapping
481 structures throughout assessments. Figure 6 presents the MFA plots comparing the three
482 evaluations for the two consumers that presented the best (C118) and worst (C121)
483 agreements between sessions. Consumer C118 performed a highly similar comparative
484 allocation of the samples in the three perceptual spaces, with high RV coefficients (RV
485 inf-blind= 0.71; RV choice-blind= 0.76; RV inf-choice= 0.86). On the contrary, the
486 perception of the samples for consumer C121 shifted notably from scenario to scenario,
487 with very low RV coefficients (RV inf-blind= 0.1; RV choice-blind= 0.1; RV inf-choice=
488 0.04). To obtain an overall view of the consumer sample, the SI (similarity index)
489 coefficients were calculated for each of the participants (Tomic, Berget & Naes, 2015).
490 SI takes a value of zero when configurations are the same as the consensus scores; the
491 higher the value, the lower the similarity. Figure 7 shows the distribution of SI values for
492 all the consumers, ranging from 0.47 to 1.11. Most consumers had SI values between
493 0.6 and 0.8. Few consumers have a much worse or much better fit than the rest,
494 suggesting that there were relatively small individual differences.

495

496 **4. General Discussion**

497 The fact that consumers might react similarly when mapping products based on their
498 preferences or choice as compared to when mapping products based on the products'
499 descriptive similarities or differences, and that these mappings might be mostly based on
500 the sensory aspects, was initially unexpected. Carrillo et al. (2012a, 2012b) had similar
501 findings when comparing results of classic blind and informed PM on biscuit samples,

502 hypothesizing that product information is in fact a “modulator” of consumer perception,
503 meaning that the perception is basically one which would be modulated depending on
504 the context **experienced by** the consumer. In this way, individual sample characterization
505 would vary within the perceptual space but the sample multivariate structure (distance
506 and relative positioning among products) would not vary dramatically. The same authors
507 found that the observed **changes** presented a **sample-dependent** effect. This was also
508 the case in the present work. When looking **at** figures 4 and 5, **it** is evident that samples
509 **B2, B5** and **B8** shifted positions considerably more than the **other** samples, while the
510 overall structure of sample configuration remained stable. In particular, **B8** was assessed
511 as very different from the rest (polarizing effect) when **assessed** with information, both in
512 the informed PM and in the PM-C. This shift **may** have **occurred** because **it was** the only
513 sample that contained barley and because of its on-pack nutritional and health claims (B-
514 glucans, lower cholesterol, long-lasting satiety). Carrillo et al. (2012a) mentioned a
515 **sample-dependent** change in perception linked to nutritional and health claims,
516 particularly when those claims were not completely understood by consumers. Added to
517 this, other authors have highlighted the importance of the fit carrier-claim (Krutulyte et
518 al., 2011), and how the perceived carrier-ingredient fit is related to the familiarity with the
519 combination and to the healthiness of the carrier food (Carrillo et al., 2012b). Barley,
520 **albeit** not an unknown **bread** ingredient for Norwegian consumers, has been re-
521 introduced in the Norwegian market in many new products accompanied by the
522 communication of various health and nutritional effects. B-glucan is also quite a new
523 functional ingredient for the Norwegian market.

524 The reported stability of sample configurations in blind and informed conditions, also
525 **demonstrated** by the present study, and the modulator effect of the context of the test,
526 make sense in an analytic descriptive framework. This is because consumers use the
527 available information to sort samples in a bi-dimensional perceptual space which would
528 subsequently **be** modified by the extra information received through the pack. Further,
529 the results of this and previous works using PM in different scenarios suggest **that** this

530 basic perceptual structure in consumers' minds would be determined **primarily** by the
531 product sensory cues and **modulated** by the extrinsic product information. This
532 modulation is expressed by tweaking the map, and mainly by using specific and distinct
533 characteristics in the descriptive step. It would be **worthwhile** to study the effect (or
534 **absence of an effect**) of this modulation in other type of studies, for example in conjoint
535 approaches, as compared to PM, looking into the interaction of intrinsic and extrinsic
536 product cues. In those tests, the information is usually displayed on a computer screen,
537 **showing** all variables with the same salience, **something that** could potentially lead to an
538 overestimation of the influence of certain parameters on food choice, as previously
539 suggested by Varela et al. (2014).

540 The idea behind **the method suggested in this paper** and some of the results of the
541 present study were presented in Eurosense 2014 and not published until now **for a range**
542 **of reasons**. In the meantime, we had the chance to conduct a second study using PM-C
543 and to compare it to CATA, to evaluate consumers' perception of a complex set of stimuli
544 **such** as aromatically enriched wines. In that recently published work (Lezaeta et al.,
545 2017), working with 150 consumers, we observed that both consumer-based methods
546 highlighted the positive effect of aromatic enrichment on consumer perception and
547 acceptance. However, PM-C generated a very detailed description in which consumers
548 focused less on the sensory aspects and more on the usage, attitudes, and reasons
549 behind their choices, providing a deeper understanding of the drivers of liking/disliking
550 of enriched Sauvignon Blanc wines. This new work confirmed what we suggested in the
551 proof of principle, which we now **elaborate on** in this work.

552 However, **prior to** these two studies, there was no experience with changing the cognitive
553 framework **of Projective Mapping** from an analytic mapping to an affective mapping, and
554 our results suggest that consumers would be performing a sort of "preference mapping
555 in their heads". To accomplish this aim, they would first map the products, as they would
556 do in a classic PM, and they would subsequently state their preferences via the
557 descriptive step, for example by describing usage and attitudes **characteristics** in

558 considerable detail. More work would be needed on this technique to assess if this can
559 be generalized to other cases. It is also possible that the affective frame of mind allowed
560 for better differentiation between the samples, through a combined effect of the
561 modulation of the extrinsic characteristics and the personal meaning added to the
562 different product dimensions (hedonic perception, usage, attitude, brand perception,
563 etc.). Indeed, in Lezaeta et al. (2017), we saw that – compared with CATA – PM-C
564 stretched the perceptual space further, with PM-C discriminating better among the wine
565 samples.

566 In the 1998 paper by King et al., comparing free and structured projective mapping (with
567 liking as one of the axes) for identification of similarity-of-use of snack bars, they did not
568 obtain a better sample discrimination through the structured PM. It is possible that a too-
569 structured mapping scenario, with predefined categories, prevented consumers from
570 freely expressing their perceptions, sorting the products into relatively obvious groups
571 rather than detailing their hedonic perception. Torri et al. (2013) studied how different
572 groups of consumers realised a classic PM test with wines, where consumers' product
573 differentiation was poor. They separated the consumers into three groups depending on
574 their performance and concluded that increased differentiation ability was observed
575 among those consumers able to match the duplicate samples in the PM test, and that
576 their main mapping dimension was highly correlated to their liking. Even if consumers
577 were asked to describe the samples and no indication of using liking as criteria was given,
578 it is possible that the high complexity of the samples pushed some consumers into using
579 their hedonic perception as a basis for categorization. Those consumers were able to
580 improve discrimination, which would be in agreement with what was reflected in our work.
581 The descriptive step in the affective approach to PM provided a much richer description
582 than the classic approach in terms of preference drivers. Consumers expanded on the
583 reasons behind sample categorization and their choices, covering things such as target
584 consumers, consumption occasions, possibilities of usage, food pairings, health-related
585 properties, brand associations and references to the price and willingness to buy/not buy.

586 In this scenario, consumers also highlighted their rejection or disliking drivers in greater
587 depth.

588

589 **5. Conclusions**

590 The results of the perceptual spaces obtained in this work comparing PM in blind and
591 informed conditions were quite comparable, suggesting that sensory cues were the main
592 driver in the categorization. In the choice-based PM, consumers focused less on the
593 sensory aspects and more on usage & attitudes, generating more detailed descriptions.
594 In this way, the affective approach to PM provided an enhanced understanding in terms
595 of the drivers of liking/disliking, making it a promising potential tool for category and
596 market exploration.

597 The limited number of consumers used in this study (n=50) did not permit drawing any
598 conclusions on implications for the bread category in the Norwegian market. This was
599 not an objective of this work, but rather a proof of principle of the approach. The clear
600 differences found when comparing PM scenarios make the data strong enough from a
601 methodological perspective, suggesting that this new approach to PM could add
602 interesting information on consumers' drivers for liking and reasons behind their choices.
603 More research is needed on further product categories to further improve understanding
604 of the complete picture.

605 It is in fact interesting how PM-C allowed for this “unfolding” in a seemingly two-step
606 processing and conveying of the information: first, a sensory description, followed by an
607 in-depth hedonic and behavioural description. This phenomenon deserves further
608 research.

609 As pointed out by some recent methodological studies in classic PM (Varela et al., 2014;
610 Vidal et al., 2016; Varela et al., 2017) it would be also worth following up the individual
611 differences and group behaviour in the PM-C.

612

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726 **Table Captions**

727 Table 1.- Bread samples included in the research

728 Table 2.- Mean OL ratings and Fisher LSD (n=50, Analysis of the differences between
729 the categories with a confidence interval of 95%)

730 Table 3.- Descriptive step in the three PM **assessments**. Chi square per cell analysis.
731 The analysis was run in the complete data table. Data are displayed in three groups
732 (sensory terms, hedonic terms and usage and attitudes terms) for better understanding.

733 (+) or (-) indicate that the observed value is higher or lower than the expected theoretical value. *** p <
734 0.001, ** p < 0.01 and * p < 0.05; effect of the chi square per cell

735 **Figure captions**

736 Figure 1.- Workflow of experiments

737 Figure 2.- **Internal** preference map, (a) product plot and (b) consumers and **attributes** plot

738 Figure 3.- Superimposed MFA representation of the eight samples. Each sample is
739 represented by four points, corresponding to the four **assessment** instances: **QDA**
740 **(generic descriptive analysis)**, PM Blind, PM Informed, PM Choice). The consensus
741 representation is represented for each of the samples as the central point.

742 Figure 4.- Multiple factor analysis of the data obtained in the two classic PM scenarios.
743 (a1) Representation of the samples in the PM Blind; (a2) Representation of the terms in
744 the PM Blind; (b1) Representation of the samples in the PM Informed; (b2)
745 Representation of the terms in the PM Informed.

746 Figure 5.- Multiple factor analysis of the data obtained in PM based on choice.
747 Representation of the samples (left) and the terms (right)

748 Figure 6.- Superimposed MFA representation of the eight samples, corresponding to the
749 three PM evaluation instances, for two individual consumers. Consumer with best
750 agreement on the left (RV inf-blind= 0.71; RV choice-blind= 0.76; RV inf-choice= 0.86)
751 and the consumer with the worst agreement on the right (RV inf-blind= 0.1; RV choice-
752 blind= 0.1; RV inf-choice= 0.04).

753 Figure 7.- Barplot showing the similarity index (SI) for all consumers. The values are
754 sorted so that the consumers **on the very left** have the smallest variation across the
755 different sessions, whereas the **consumers on the very right** have large variation across
756 the sessions.

757