

Projective mapping based on choice or preference: an affective approach to projective mapping

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Accepted Version

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(2017) Projective mapping based on choice or preference: an affective approach to projective mapping. *Food Research International*, 100 (Part 2). 241 - 251. ISSN 0963-9969
Available at <https://centaur.reading.ac.uk/76523/>

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Published version at: <http://www.sciencedirect.com/science/article/pii/S0963996917305094>

Publisher: Elsevier

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

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

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

30 **1. Introduction**

31 Projective mapping (also known as Napping®) followed by a descriptive step has been
32 extensively used in the last years as an alternative tool for the description of products
33 and packs with consumers. It is considered a holistic approach to product profiling,
34 somehow closer to what happens in a choice event when compared to classic
35 descriptive or attribute-based techniques (Varela & Ares, 2012; Valentin et al., 2012).
36 Built on the perception of similarities and differences, it encourages the generation of a
37 global representation of the products, which is usually hindered when consumers are
38 directly asked about multiple particular attributes. Holistic methods enable to identify
39 the main attributes responsible for the differences in the samples without forcing
40 consumers to focus on specific characteristics (Ares & Varela, 2012). In addition,
41 projective methods allow obtaining more spontaneous responses than other more
42 directive techniques (Guerrero et al., 2010). The projective mapping (PM) task can
43 involve the perception of similarities and differences from an intrinsic (sensory) or
44 extrinsic (pack, labelling, etc.) perspective, or both (Carrillo, Varela, & Fiszman, 2012a),
45 generally considering product objective characteristics for categorization rather than
46 liking as main parameter. Nevertheless, consumers often use hedonics or benefit-
47 related terms together with the product and pack descriptive characteristics; which can
48 be relevant for relating product characteristics to marketable features and consumer
49 preferences (Ares & Varela, 2012). This approach has been applied with success to
50 explore sensory and non-sensory stimuli, like the influence of packaging information as
51 nutritional and health claims on consumers' perception (Carrillo et al., 2012a; Carrillo,
52 Varela, & Fiszman, 2012b; Miraballes et al., 2014; Varela et al., 2014).
53 When optimizing food products, the general practice has been to ask consumers about
54 liking while the sensory properties would be characterized in parallel by a trained panel,
55 in a preference mapping type of exercise (van Kleef et al. 2006). However, trained
56 assessors may describe the product differently, so sensory characterization based on
57 consumers direct input might potentially have greater external validity (Ares & Varela,

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58 2012). In this sense, overall liking (OL) has been gathered together with PM data in
59 some studies for concluding on drivers of liking (Ares et al, 2010; Torri et al., 2013) and
60 to better understand the changes in hedonic response in different mapping scenarios
61 (Carrillo et al., 2012b). In a study by Ares et al. (2011), consumers were asked about
62 their ideal product to be mapped, after doing a PM with real samples of powdered
63 orange juice. The results were similar than those of external preference mapping.
64 Withers et al. (2014) have used taxonomic sorting, a holistic method also based on
65 sample categorization, to generate diagnostic sensory data directly from target
66 consumers by external preference mapping. Generally, hedonic descriptions or OL
67 have been considered as supplementary variables in PM data.

68 From a different perspective, King, Cliff & Hall (1998) compared PM to a “structured
69 PM” to map snack bars, where they used labeled axes in the PM space: the x-axis was
70 defined as “liking” (low - high) and the y-axis as “use” (treat - meal replacement). They
71 found the proposed method less discriminating than PM, but only 24 consumers
72 participated in this study. To our knowledge, there have not been other approaches to
73 PM from an affective perspective, with liking or preference explicitly driving the
74 categorization of the samples.

75 Consumers in affective tests act in an integrative fashion, basing on a global sensory
76 and non-sensory stimulation from the product - in contrast to the analytical testing
77 frame of mind in descriptive testing (Lawless & Heymann; 2010; Jaeger, 2006). More
78 concretely, since consumers are integrated and organised wholes, as highlighted by
79 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., n.d.). Thus, consumers would cognitively focus
82 on products differently when describing, than when 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.

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85 The objective of this study was to explore a new affective approach to projective
86 mapping, with bread as case study, basing product categorization on consumers'
87 choice or preference, and to compare it to the classic preference mapping approach.
88 This approach might provide information that is more realistic for product developers
89 and marketers during the process of product development and launch in the market.

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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 of the south of Oslo region (Norway). Products differed in terms of
95 brands, prices, mix of grains used and percentage of wholegrain (Table 1).

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

98 A trained panel of nine assessors at Nofima Mat (Aas, Norway) performed a sensory
99 descriptive analysis according to a quantitative descriptive analysis (QDA) as described
100 by Lawless and Heymann (2010) as generic descriptive analysis. The assessors were
101 tested, selected and trained according to ISO standards (ISO, 1993), and the sensory
102 laboratory used followed the ISO standards (ISO, 1988). The assessors agreed upon
103 25 attributes describing the bread samples: odour intensity, hue, colour intensity,
104 whiteness, pore size (crumb), amount of seeds/fibres (crust), roughness, elasticity,
105 strength, crumbling, cohesiveness (using the finger), acidic taste, sweetness, saltiness,
106 bitterness, yeast flavour, grain flavour, nut/seed flavour, roasted flavour, rancid flavour,
107 hardness, juiciness, roughness/coarseness, chewiness and stickiness. All attributes
108 were evaluated on unstructured line scales with labelled endpoints going from “no
109 intensity” to “high intensity”. In a pre-test session, the assessors were calibrated on
110 samples that were considered the most different on the selected attributes typical for
111 the breads to be tested. Samples were served in transparent Ziploc® bags labelled with
112 three-digit numbers. Tap water was available for palate cleansing. Two replicates were

113 performed for each bread sample. All samples and replicates were served in
114 randomised order following a balanced block experimental design.

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116 **2.3 Consumer tests**

117 Two sessions, one-week apart, were held with the same group of participants and the
118 same eight samples at Nofima Mat (Aas, Norway). In the first session, consumers
119 performed two “classic” PM tests: blind PM (tasting blind samples) and informed PM
120 (tasting together with the pack). In the second session, consumers first rated blind
121 overall liking and after that, they performed a PM task based on choice or preference,
122 in informed conditions (tasting together with the pack). In both sessions new samples
123 with new codes were delivered for the two tests; consumers had a 15 minutes break
124 between tests.

125 **2.3.1 Consumers’ sample**

126 The consumers included in the study (n=50) were recruited from Nofima’s consumers
127 database, they were frequent consumers of wholemeal bread (more than twice per
128 week). The participants were between 34 and 64 years old (43y.o in average). Each
129 session lasted around 30 min (Figure 1).

130 **2.3.2 Session 1 – Classic PM, blind and informed**

131 All participants were instructed in the use of the PM technique with a descriptive step.
132 The basics of the technique were explained to the participants through an example
133 employing geometric shapes with different colours and patterns, without any mention to
134 breads. After the explanation of the technique, the participants received an A2 sheet of
135 paper to allocate the samples. Samples were allocated according to the principle that
136 samples with similar characteristics should be placed close to each other, while
137 different samples should be placed farther away. Next, they had to write all the terms
138 they perceived in connection with each sample, or group of samples, on the sheet,
139 beside the position of the respective samples (technique also known as ultra-flash
140 profiling).

141 **Blind PM**

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2 142 The eight bread samples were presented simultaneously for direct comparison. Each
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4 143 sample was presented in a transparent Ziploc® bag coded with 3-digit numbers on a
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6 144 sticker. This type of presentation facilitated the location of the samples on the A2 sheet.
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8 145 The participants had to observe, smell and taste the breads, and then placed the
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10 146 samples on the A2 sheet. Once they decided on the positioning, they should write the
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12 147 codes on the sheet, and write the terms describing the perceived characteristics of the
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14 148 sample or group of samples close to the corresponding code.
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17 149 **Informed PM**

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19 150 The participants simultaneously received the eight bread samples as in the blind test,
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21 151 but this time each with an accompanying scan of the original front-of-pack (FOP),
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23 152 printed in colour. All scans of the FOP had the same dimensions. The participants
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25 153 performed the test in the same way as in the blind test, but this time they had to
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27 154 consider both the information received, and the sensory characteristics perceived. As
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29 155 before, they had to position the codes of the samples on the A2 sheet, and write the
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31 156 descriptive terms.
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35 157 **2.3.3 Session 2 (one week apart) – Blind overall liking rating and informed PM**
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37 **based on choice or preference (PM-C)**

38 159 **Blind overall liking rating**

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41 160 Consumers rated their overall liking in 9-point box hedonic scales. Samples were
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43 161 evaluated in blind conditions in a rotated presentation balanced for order and carry-over
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45 162 effects (Wakeling & MacFie, 1995).
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49 163 **Informed PM based on choice or preference (PM-C)**

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51 164 Samples were presented the same way as in the informed PM (bread samples with an
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53 165 accompanying front-of-pack), but using different codes. The instructions of this test
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55 166 differed from the “classic” PM approach in the way in which consumers had to base
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57 167 their categorization and sample allocation. Instructions were as follows: “*Please*
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59 168 *evaluate the samples and look at the packs and position them on the sheet according*
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169 *to their differences and similarities basing your criteria on what you would choose,*
170 *thinking about different food occasions. Place them on the sheet in such a way that two*
171 *samples are close to each other if they're similar with regards to your preference and*
172 *two samples are far from each other if they are different with regards to your*
173 *preference.”* As in the other two tests, consumers had to write the codes of the samples
174 on the A2 sheet together with descriptive terms.
175 These instructions were fine-tuned through a pilot test session, and subsequent open
176 discussion with the consumers participating in the trial (n=10). As an example, a
177 reference was added in the instructions stressing “*what you would choose, thinking*
178 *about different food occasions*” to avoid consumers thinking they should rank the
179 samples from most to least preferred, and take the decision on only one consumption
180 situation. In this way they understood they could for example like two or more breads
181 equally, but decide to consume them in different occasions or for different applications.
182 Also, the categorization basis was stressed when instructing them to place samples as
183 “*two samples are close to each other if they're similar with regards to your preference*”
184 (and conversely). In this sense, an example was given to the consumers by using a
185 very different food category: sweet foods/desserts where the possibility of giving
186 multiple reasons behind their choice was further explained. In the example consumers
187 had different desserts like fresh fruit, yogurt, a gooey cake, etc. so they better
188 understood the idea.

2.4. Data analysis

2.4.1 Analysis of the trained panel data

192 Analysis of variance (ANOVA) using a two-way model with interactions and with the
193 assessor and interaction effects considered random, was performed on the descriptive
194 sensory data from the trained panel in order to identify the sensory attributes that
195 discriminated between samples. A PCA on the average of the sensory descriptive data

196 (significant attributes, $p < 0.05$) was performed (mean centred data, no
197 standardisation).

198 **2.4.2 Analysis of the consumer tests data**

199 Analysis of variance (ANOVA) was performed on consumer overall liking scores
200 considering consumer and sample as sources of variation. Mean ratings were
201 calculated and significant differences were checked using Fisher's LSD test ($p < 0.05$).
202 Agglomerative hierarchical clustering (HCA. Dissimilarity: Euclidean distance;
203 Agglomeration method: Ward's method) was utilized as segmentation procedure in
204 order to highlight groups of consumers with different liking patterns. Furthermore, an
205 internal preference mapping was achieved via PCA (Principal Component Analysis) of
206 a matrix of products x consumers, for obtaining a multidimensional representation of
207 products and consumers in order to check against the clustering results (Varela, 2014).
208 Analysis of variance (ANOVA) and Fisher's test were also run for the clusters obtained,
209 same way as above.

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

219 To study if consumers grouped/mapped the samples differently in the three PM
220 sessions, an MFA was conducted for the three tables for each consumer. Then the
221 variability between the consensus of the three sessions was measured by the similarity
222 index proposed in (Tomic et al) . The similarity index (SI) for individual k ($k = 1, \dots, n$) is
223 computed as:

$$SI_k = \frac{1}{n} \sum_{i=1}^n \frac{\|F_{ki} - F_k\|}{F_k}$$

224

225 Here $\| \cdot \|$ is the frobenius norm, F_k the consensus obtained with A=2 components for
 226 consumer k, and F_{ik} the projected coordinates of consumer k from session i (i=1,2,3).

227 The SI aims to measure the variation around the consensus, and it is clear from the
 228 equation above that higher SI values indicate that the consumer maps samples
 229 different in the three sessions. There is no upper limit on SI, but a value > 1 indicates
 230 that residuals are larger than the variation between the samples within the consensus.

231 The SI can also be computed for the complete data set in one session to measure the
 232 overall agreement of the consensus.

233 All the words provided by the participants in the description phase of the PM were
 234 analyzed qualitatively. The terms generated to describe the samples were grouped by
 235 consensus between two researchers, considering synonymous and derived words.
 236 Terms mentioned by at least 5% of the consumers were retained for further analysis
 237 (Symoneaux, Galmarini, & Mehinagic, 2012). The frequency table containing the terms
 238 was considered as a set of supplementary variables in the MFA of the PM data. The
 239 frequency of mention was determined by counting the number of mentions of the same
 240 term in each session.

241 Global Chi-square was used for testing homogeneity of the contingency table of the
 242 terms generated in the descriptive step of the PM in the three scenarios (Symoneaux et
 243 al., 2012). When the initial Chi-square was significant, a chi-square per cell was done
 244 within each cell identifying the source of variation of the global Chi-square.

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

247 The chi-square per cell analysis was run with an XL macro as in Symoneaux et al.
 248 (2012).

1
2 249 The rest of the statistical analyses were run in XLStat statistical software package
3 250 2014, Addinsoft, New York.

4 251

6 252 **3. Results**

8 253 It is important to point out that the objective of this methodological research was not to
9 254 draw conclusions on the products themselves, but on how the different approaches to
10 255 PM (analytical and affective) influenced on the product descriptions, and product choice
11 256 information.

12 257

19 258 **3.1. Overall Liking & liking patterns**

21 259 Overall liking (OL) significantly varied between bread samples (Table 2), ranging from
22 260 4.1 to 5.9. Preference responses are usually heterogeneous, and mean scores are not
23 261 always representative of real preference patterns (MacFie, 2007; Felberg et al. 2010).
24 262 Preference mapping approaches could be applied to understand consumer preference
25 263 patterns and together with sensory data, to look for underlying dimensions that drive
26 264 consumer preferences (Varela, 2014). In this first section, hierarchical cluster analysis
27 265 (HCA) and the sensory description via generic descriptive analysis by the trained panel
28 266 were combined to understand the liking patterns. Cluster analysis could be seen as “the
29 267 lowest level of preference mapping” (Mac Fie, 2007).

30 268 HCA highlighted three clusters, one of them composed of only 5 consumers who
31 269 rejected all samples (scores 4 and under). Considering they disliked the general
32 270 category under study, the analysis was continued on the other 2 clusters. Table 2
33 271 displays the distinct liking patterns of those two clusters. Although both groups of
34 272 consumers rejected sample **B8**, liking patterns were clearly different. **B8** (barley, extra-
35 273 coarse), was described by the trained panel as with a somehow strange, rancid flavor
36 274 that could have explained the general consumer rejection.

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275 Cluster 1 was less discriminating among samples, they rejected **B8** and did not present
276 significant differences in overall liking amongst the rest of the samples, they were fairly
277 open to any kind of bread but slightly preferred whiter, more cohesive breads.

278 Consumers in cluster 2 on the other hand, had more defined preferences, favouring
279 dark, rough breads, and rejecting whiter, less coarse varieties. **B1** (wholegrain, half-
280 coarse) and **B5** were top liked, which were described as with intense odor, bitter, with
281 nut/seed and roasted flavour, rough, with big pores and dark; followed by **B2** and **B7**
282 (rye, extra-coarse), described as chewy, rough, sweet, roasted, dark and strong. They
283 clearly rejected **B3** and **B4** (whiter, cohesive, sticky, crumbling, with yeast taste, grain
284 taste and salty), added to the rejection of **B8**.

285 These liking patterns could also be observed by looking into the multidimensional
286 representation of products and consumers in an internal preference map (Figure 2).

287 In the following sections the obtained two clusters will be explained by the descriptive
288 data obtained by PM with consumers, to contrast with the interpretation provided by the
289 QDA. The conclusions that can be drawn with preference mapping approaches, using
290 classic descriptive data and overall liking together, are limited to the sensory drivers of
291 liking or disliking. The use of projective techniques as PM may allow for getting a
292 description further than sensory terms, so preference mapping approaches based on
293 PM can unveil other reasons behind the affective response patterns (Ares et al., 2011;
294 Varela & Ares, 2012).

295

296 **3.2. Classic PM vs the new affective approach for understanding consumers** 297 **perception**

298 **3.2.1. Perceptual spaces - spatial configurations**

299 ***Comparisons of the four evaluations***

300 Sample configurations in the four tasting instances (descriptive analysis with the trained
301 panel and the three PM with consumers) were highly correlated, with RV coefficients
302 ranging from 0.86 to 0.97. QDA presented the lowest RVs with respect to all the PM

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303 scenarios, but they were still good (0.86). This can also be appreciated from the
304 superimposed representation of the samples in the multiple factor analyses (Figure 3).
305 For most of the samples, QDA was further away in the perceptual space to the
306 consensus, but still keeping a similar relative positioning between samples. These
307 results suggest that consumers might react similarly when assessing products blindly
308 and informed, and even when basing on their preference rather than on the products'
309 descriptive characters. Moreover, the high correlations to QDA indicate that the
310 assessments are mostly based on the sensory aspects.

311 In the descriptive step of blind PM , consumers generated 75 different terms in total to
312 describe the sample set, comprising mainly sensory terms (47) but also hedonic and
313 some related to usage and attitudes. In the descriptive step of the informed PM,
314 consumers generated also 75 different terms in total, again a majority of sensory terms
315 (42) and some hedonic and related to usage and attitudes. The fact that consumers
316 focused more on sensory cues to describe similarities and differences between the
317 samples rather than on usage or others goes in accordance with the high correlation
318 obtained with the QDA and both classic PM tests.

319 In the descriptive step of the PM based on choice or preference, consumers generated
320 approximately the same amount of different terms in total (78), however, in this
321 scenario the number of sensory terms was significantly lower (28) and the description
322 was more focused on the usage and attitudes category of terms (39). This shows that
323 although the positioning of the products in the perceptual space might have been
324 similar, the associations consumer made when thinking about their preference or
325 choice for different consumption occasions was different, and mainly driven by the
326 usage and the situation, rather than by specific sensory cues.

327 **Blind PM**

328 Figure 4 shows the perceptual spaces as described by the two first dimensions of the
329 MFA of the two classic PM in both scenarios (blind and informed). In the blind PM
330 (Figure 4 a1 and a2), the two first dimensions of the MFA display 50% of the variability

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331 of the original data. Looking together into samples configuration (Figure 4 a1) and their
332 description (Figure 4 a2), the breads were grouped mainly based on cereal type (oats,
333 rye, barley, with wholegrain and combinations middle-way in the map), as well as fibre
334 content and healthiness perception. Consumers attached a healthier perception to the
335 samples described as coarser and with more seeds taste (**B7, B5, B1**), while attached
336 a more standard or ordinary characters to the softer samples towards the other side of
337 the first factor.

338 ***Informed PM***

339 In the informed, classic PM: it is clearly visible from the sample configuration (Figure 4
340 b1), that the information polarized the results obtained for sample **B8**, which was
341 separated from the rest of the samples in the consensus configuration. Evidently, the
342 somehow unique characteristics of this sample, particularly the “off-flavour” described
343 by some in the blind PM evaluation (Figure 4 a2) - in line with the “rancid” in QDA -
344 made more sense in consumer minds when knowing more about this bread, and
345 together with mentioning the base cereal (barley and claims), they focused more on
346 describing the bad, off-taste, and mapped it further away than the rest. As B8 spans
347 factor 2 of the MFA; the other samples do not show much variation in this direction. The
348 first factor showed the variation of samples “from rye (**B7**) to oats (**B6, B4**)” with the
349 wholegrain and mixes in the middle. However, variations in coarseness and darkness
350 are seen in this factor. The breads perceived as less coarse, or whiter are located
351 towards the right of the plot. It is interesting to see, that the information on the whole
352 grain content, did not noticeably affect the perception of coarseness, attached to **B7**
353 and **B5** (extra coarse), but also to **B1** (half coarse).

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

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

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359 **B6** and **B4**, both made mainly with oats, were the only ones not discriminated in this
360 tasting instance. In the PM-C consumers used more words, and less were on sensory
361 descriptions. The extra information obtained with this type of PM approach can be
362 appreciated in Figure 5 by interpreting the particular description of each sample
363 (descriptive step), which can also be used to better understand the liking patterns as
364 highlighted by consumers. As an example, Cluster 2 preferred samples **B1**, **B2**, **B5** and
365 **B7**, described in PM-C as dark, tasty, with good texture, a good/exciting taste, with
366 corn, seeds and taste of seeds, sour, coarse, heavy, satiating, rich in fibre, healthy,
367 sporty, for adults, of a known brand, somehow expensive, good for dinner, with soup or
368 cheese, and they would buy them. On the other hand, consumers in Cluster 1 tended to
369 like more chewy breads with smooth surface, without whole seeds, not as coarse, with
370 oats, less tasty or even bland, good when toasted, a low price, everyday bread, for
371 lunchbox, easily eaten, for families, for children. Meanwhile, these characteristics were
372 rejected by cluster 2. The PM-C also helped to further understand the rejection of **B8** by
373 all consumers. It was described as not attractive, with bad, strange taste, off-flavour
374 and odour, bitter, fluffy and porous and it was perceived as unhealthy, consumers
375 stated they would not buy this kind of bread. This supports the idea of the differentiated
376 drivers of consumers' description in this case, by the usage occasions and the
377 situation, and only some important sensory cues

42 ***Descriptive step***

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379 Table 3 shows the list of terms mentioned by consumers in the three PM scenarios
380 together with the Chi Square per cell analysis. The terms included in the analysis were
381 the ones cited at least by 10% of the consumers for one product.

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

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387 seeds/taste of seeds. In the informed PM, the sensory terms were less in total, but the
388 most mentioned were mainly the same, however, juicy and smooth surface became
389 also important in this scenario to describe the samples. In the PM-C, the total number
390 of sensory terms was significantly lower (28) and the terms elicited by consumers with
391 high frequency were less. The words bland, corn and dry were still mentioned more
392 than 40 times, but significantly less frequently than in the blind scenario. However,
393 coarseness was mentioned significantly more frequently, going from 44 mentions in the
394 blind PM to 106 mentions in the affective approach (PM-C); this suggests coarseness
395 might have been one of the most important drivers of product differentiation when
396 thinking about choosing, in this particular sample set.

397 The **hedonic terms** category was the one with less distinct terms generated by
398 consumers in the three PMs, and the frequencies were also lower. In general, in the
399 blind PM there were significantly more terms regarding liking or disliking of some
400 sensory characteristics, as: exciting appearance, good smell, standard appearance and
401 standard texture, however the number of mentions were low (25 or less). The hedonic
402 term most mentioned in the three PM was good/exciting taste, but there were no
403 differences between them (86-101 mentions). It is quite interesting how two of the
404 hedonic terms significantly increased in the PM-C, bad taste and would not
405 buy/eat/uninterested became very important in the affective approach, which suggests
406 that consumers were more prone to express their opinions with regards to disliking
407 when grouping the samples based on what they would choose.

408 The category of descriptions on **usage & attitudes** was the one more influenced by the
409 scenario. The number of different terms generated in total more than doubled in the
410 affective approach to PM (from 15 in blind to 39 in the affective approach), and the
411 frequencies of mention of usage & attitudes terms were significantly higher. The terms
412 generated included: target consumers (for kids, for adults, for family), consumption
413 occasions (for breakfast, lunch, dinner, everyday bread, for lunch-box, for sport), food
414 pairings (for soup, with cheese, with toppings, with jam, versatile), health related

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415 properties (healthy, satiating, weight reducing), references to the brand (good label,
416 standard label), and to the price (expensive, low price). It is interesting to highlight how
417 the price references were almost inexistent in the classic PM scenarios (both blind and
418 informed), and how the references to healthiness increased significantly, further than
419 focusing much more in the possibilities of usage of the product.

420 Chi square per cell was also run on the term by product matrix in each scenario, to
421 being able to highlight the different profiles of each sample (data not shown). As stated
422 above, the main objective of this paper was not to describe the samples, but the the
423 study shown that the terms generated by each individual product in the affective PM
424 highlighted the important attributes for each sample at the light of the different
425 preference patterns. As an example, **B8** was associated significantly more frequently
426 with the terms would not buy, bad taste, weird taste, off flavour, sour taste and non-
427 informative label. Hence it becomes clear why the product was rejected by most
428 consumers, highlighting the drivers of disliking. On the contrary, **B5**, the bread liked by
429 both groups of consumers, was associated more frequently as with a good/exciting
430 taste, tasty, with good smell and good tasting crust, and consumers found it both good
431 as lunch box bread and also sporty. In terms of coarseness, it was significantly
432 associated with this concept, but not significantly different to **B7**, which was at the same
433 time significantly more seen as a dark bread, for adults and highly satiating. This
434 suggest that **B5** could be a good option for both clusters within the coarser breads,
435 while **B7** was very well liked by Cluster 2 but within the less liked in Cluster 1.

437 **3.4. Consumers' individual behaviour in the different PM scenarios**

438 A natural question that might be raised at this point is how different consumers, or
439 groups of consumers, reacted to the change in PM scenario. When comparing how
440 samples were located in the perceptual spaces by both liking clusters in the different
441 tests, they were also very similar; for example comparing the relation of the perceptual
442 spaces obtained by clusters 1 and 2 in the PM-C, RV was 0.882. Something similar

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443 happened when comparing the outcomes for the same cluster throughout scenarios; for
444 instance, Cluster 1 had an RV of 0.828 between PM blind vs PM-C. These results
445 showed that the maps obtained for the groups with similar liking patterns were quite
446 stable throughout different PM tests. However, that was not necessarily the case when
447 studying consumers' individual behaviour. Some of the consumers changed their maps
448 drastically from one scenario to another, while some others maintained their mapping
449 structure very stable throughout evaluations. Figure 6 presents the MFA plots
450 comparing the three evaluations for the two consumers that presented the best (C118)
451 and worst (C121) agreements between sessions. Consumer C118 performed a highly
452 similar comparative allocation of the samples in the three perceptual spaces, with high
453 RV coefficients (RV inf-blind= 0.71; RV choice-blind= 0.76; RV inf-choice= 0.86). On the
454 contrary, the perception of the samples for consumer C121 shifted importantly from
455 scenario to scenario, with very low RV coefficients (RV inf-blind= 0.1; RV choice-blind=
456 0.1; RV inf-choice= 0.04). To have an overall view of the consumer sample, the SI
457 (similarity index) coefficients were calculated for each of the participants (Tomic, Berget
458 & Naes, 2015). SI takes a value of zero when configurations are the same as the
459 consensus scores, and the higher the value, the lower the similarity. Figure 7 shows the
460 distribution of SI values for all the consumers, ranging from 0.47 to 1.11, most
461 consumers had SI values between 0.6 and 0.8. Few consumers have a much worse or
462 much better fit than the rest. This shows that there are relatively small individual
463 differences here as compared to the Tomic example, where SI values were as higher
464 as 4.5.

466 **4. General Discussion**

467 The fact that consumers might react similarly when mapping products based on their
468 preferences or choice as compared to when they do based on the products' descriptive
469 similarities or differences, and that these mappings might be mostly based on the
470 sensory aspects, was somehow initially surprising. Carrillo et al. (2012a, 2012b) had

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471 similar findings when comparing results of classic blind and informed PM on biscuit
472 samples, hypothesising that product information is in fact a “modulator” of consumer
473 perception, meaning that the perception is basically one which would be modulated
474 depending on the context the consumer experienced. In this way, individual sample
475 characterization would vary within the perceptual space but the sample multivariate
476 structure (distance and relative positioning among products) would not vary
477 dramatically. The same authors found that the changes observed presented a sample-
478 dependant effect. This was also the case in the present work. When looking into figures
479 4 and 5 is evident that samples **B2**, **B5** and **B8** shifted positions considerably more
480 than the rest of the samples, while the overall structure of sample configuration
481 remained stable. In particular, **B8** was assessed as very different from the rest
482 (polarizing effect) when evaluated with information, both in the informed PM and in the
483 PM-C. This shift might have happened because of being the only sample that contained
484 barley, and because of its on-pack nutritional and health claims (B-glucans, lower
485 cholesterol, long lasting satiety). Carrillo et al. (2012a) mentioned a sample-dependant
486 change in perception linked to nutritional and health claims, particularly when those
487 claims were not completely understood by consumers. Added to this, other authors
488 have highlighted the importance of the fit carrier-claim (Krutulyte et al., 2011), and how
489 the perceived carrier-ingredient fit is related to the familiarity with the combination and
490 to the healthiness of the carrier food (Carrillo et al., 2012b). Barley, even if not an
491 unknown ingredient in bread for Norwegian consumers, has been re-introduced in the
492 Norwegian market in many new products accompanied by the communication of
493 various health and nutritional effects. B-glucan is also quite a new functional ingredient
494 for the Norwegian market.

495 The reported stability of sample configurations in blind and informed conditions, also
496 shown by the present study, and the modulator effect of the context of the test, make
497 sense in an analytic descriptive framework. This is because consumers use the
498 available information to sort samples in a bi-dimensional perceptual space, which would

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499 be subsequently modified by the extra information received through the pack. Further to
500 this, the results of this and previous works using PM in different scenarios, suggest this
501 basic perceptual structure in consumers' minds would be determined mainly by the
502 product sensory cues and attuned by the extrinsic product information. This modulation
503 is expressed by tweaking the map, and mainly by using specific and distinct
504 characteristics in the descriptive step. It would be worthy to study the effect (or not) of
505 this modulation in other type of studies, for example in conjoint approaches, as
506 compared to PM, looking into the interaction of intrinsic and extrinsic product cues. In
507 those tests, the information is usually displayed on a computer screen, with all variables
508 with the same salience, which could potentially lead to an overestimation of the
509 influence of certain parameters on food choice, as previously suggested by Varela et al.
510 (2014).

511 The idea behind this method and some of the results of the present study were
512 presented in Eurosense 2014 and for different reasons not published until now. In the
513 meantime, we had the chance to conduct a second study using PM-C and to compare it
514 to CATA, to evaluate consumers' perception of a complex set of stimuli as aromatically
515 enriched wines. In that recently published work (Lezaeta et al., 2017), working with 150
516 consumers, we observed that both consumer-based methods highlighted the positive
517 effect of aromatic enrichment on consumer perception and acceptance. However, PM-
518 C generated a very detailed description in which consumers focused less on the
519 sensory aspects and more on the usage, attitudes, and reasons behind their choices,
520 providing a deeper understanding of the drivers of liking/disliking of enriched Sauvignon
521 Blanc wines. This new work confirmed what we suggested in the proof of principle,
522 which we now detail in this work.

523 However, before these two studies, there was no experience with changing the
524 cognitive framework when realising PM, from an analytic mapping to an affective
525 mapping, and our results suggest that consumers would be somehow performing a
526 "preference mapping in their heads". To accomplish this aim, they would first map the

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527 products, as they would do in a classic PM, and they would subsequently state their
528 preferences via the descriptive step, for example by the description of usage and
529 attitudes characters much in detail. More work would be needed using this technique to
530 assess if this is generalizable to other cases. It is also possible that the affective frame
531 of mind allowed a better differentiation between the samples, through a combined effect
532 of the modulation of the extrinsic characteristics and the personal meaning added to the
533 different product dimensions (hedonic perception, usage, attitude, brand perception,
534 etc.). In Lezaeta et al. (2017), we indeed saw that PM-C stretched the perceptual space
535 further as compared to CATA, with PM-C discriminated better among the wine
536 samples.

537 In the 1998 paper by King et al. where they compared free and structured projective
538 mapping (with liking as one of the axis) for identification of similarity-of-use of snack
539 bars, they did not obtain a better sample discrimination through the structured PM. It
540 could have happened that a too structured mapping scenario, with predefined
541 categories, prevented consumers to freely express their perception, sorting the
542 products into rather obvious groups instead of detailing their hedonic perception. Torri
543 et al. (2013) studied how different groups of consumers realised a classic PM test with
544 wines, where product differentiation by consumers was poor. They separated the
545 consumers in three groups depending on their performance and concluded that an
546 increased differentiation ability was observed for those consumers able to match the
547 duplicate samples in the PM test, and that their main mapping dimension was highly
548 correlated to their liking. Even if consumers were asked to describe the samples and no
549 indication of using liking as criteria was given, it might have been that the high
550 complexity of the samples pushed some consumers into using their hedonic perception
551 as a basis for categorization. Those consumers were able to get a better discrimination,
552 which would be in agreement to what was reflected by our work.

553 The descriptive step in the affective approach to PM provided a much richer description
554 than the classic approach, in terms of drivers of preferences. Consumers expanded on

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555 the reasons behind sample categorization and their choices, covering things as target
556 consumers, consumption occasions, possibilities of usage, food pairings, health related
557 properties, brand associations and references to the price and willingness to buy/not
558 buy. Consumers also highlighted their drivers of rejection or disliking more in depth in
559 that scenario.

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561 **5. Conclusions**

562 The results of the perceptual spaces obtained in this work comparing PM in blind and
563 informed conditions were quite comparable, suggesting sensory cues were the main
564 driver for the categorization. In the PM based on choice, consumers focused less on
565 the sensory aspects and more on the usage & attitudes, generating a more detailed
566 description. In this way, the affective approach to PM provided an enhanced
567 understanding in terms of the drivers of liking/disliking, appearing as a promising tool
568 for category and market exploration.

569 The limited number of consumers used in this study (n=50) did not allow to draw
570 conclusions about implications for the bread category in the Norwegian market,
571 although this was not an objective of this work, but a proof of principle of the approach.
572 However, the clear differences found when comparing the PM make these data strong
573 enough from a methodological point of view, to suggest this new approach to PM could
574 add up interesting information when looking into consumer feedback on drivers of liking
575 and reasons behind their choices. More research is needed on further product
576 categories to better understand the complete picture.

577 It is indeed interesting how PM-C, allowed for this “unfolding” on a seemingly 2-step
578 processing and conveying of the information: firstly a sensory description followed by
579 an in depth hedonic and behavioural description, this deserves further research.

580 It will be also worth following up the individual differences and group behaviour in the
581 PM-C which has also been pinpointed by some latest methodological studies in classic
582 PM (Varela et al., 2014; Vidal et al., 2016; Varela et al., 2017).

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584 **Acknowledgements**

585 Thanks to Merete Rorvik and Heidi Birkelund from Coop Norge for support with sample
586 selection. The authors would also like to thank for the financial support received from
587 the Norwegian Foundation for Research Levy on Agricultural Products FFL, through the
588 research program “FoodSMaCK, Spectroscopy, Modelling and Consumer Knowledge”
589 (2017-2020), and the Research Council of Norway through the RapidCheck project.
590 Thanks also to the European Commission through the Marie Curie Actions Intra
591 European Fellowship (IEF), call FP/-PEOPLE-I2012-IEF – project title “Innovative
592 Methodologies for New Food Product Development: combining Sensory Science and
593 Experimental Economics – NEFOMET” for the support.

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698 **Table Captions**

699 Table 1.- Bread samples included in the research

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

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

705 (+) or (-) indicate that the observed value is higher or lower than the expected theoretical value. *** p <
706 0.001, ** p < 0.01 and * p < 0.05; effect of the chi square per cell

707 **Figure captions**

708 Figure 1.- Workflow of experiments

709 Figure 2.- Internap preference map, (a) product plot and (b) consumers and attributes
710 plot

711 Figure 3.- Superimposed MFA representation of the eight samples. Each sample is
712 represented by four points, corresponding to the four evaluation instances (QDA, PM
713 Blind, PM Informed, PM Choice). The consensus representation is represented for
714 each of the samples as the central point.

715 Figure 4.- Multiple factor analysis of the data obtained in the two classic PM scenarios.
716 (a1) Representation of the samples in the PM Blind; (a2) Representation of the terms in
717 the PM Blind; (b1) Representation of the samples in the PM Informed; (b2)
718 Representation of the terms in the PM Informed.

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

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

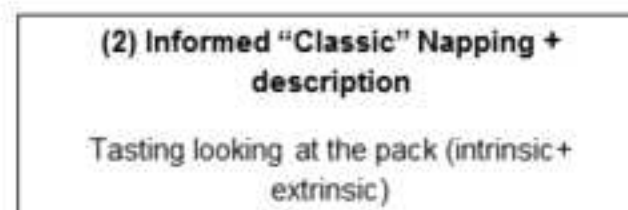
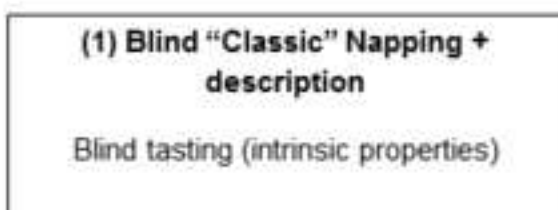
726 Figure 7.- Barplot showing the similarity index (SI) for all consumers. The values are
727 sorted so that the leftmost consumers have the smallest variation across the different
728 sessions, whereas the rightmost have large variation across the sessions.

729

Figure 1

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CONSUMER TEST - SESSION 1 (n=50)



CONSUMER TEST - SESSION 2 (n=50)

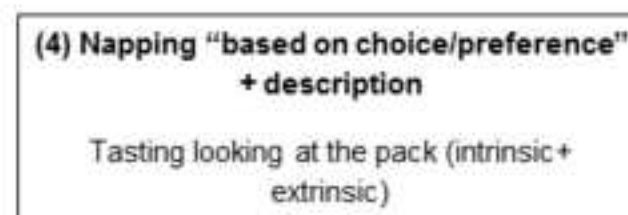
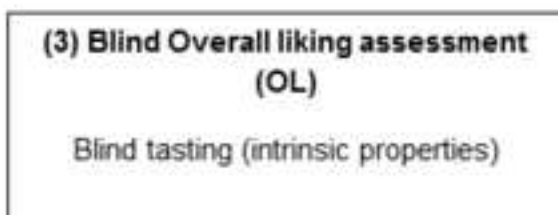


Figure 2a

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Prefmap | liking data - ConsumerCheck

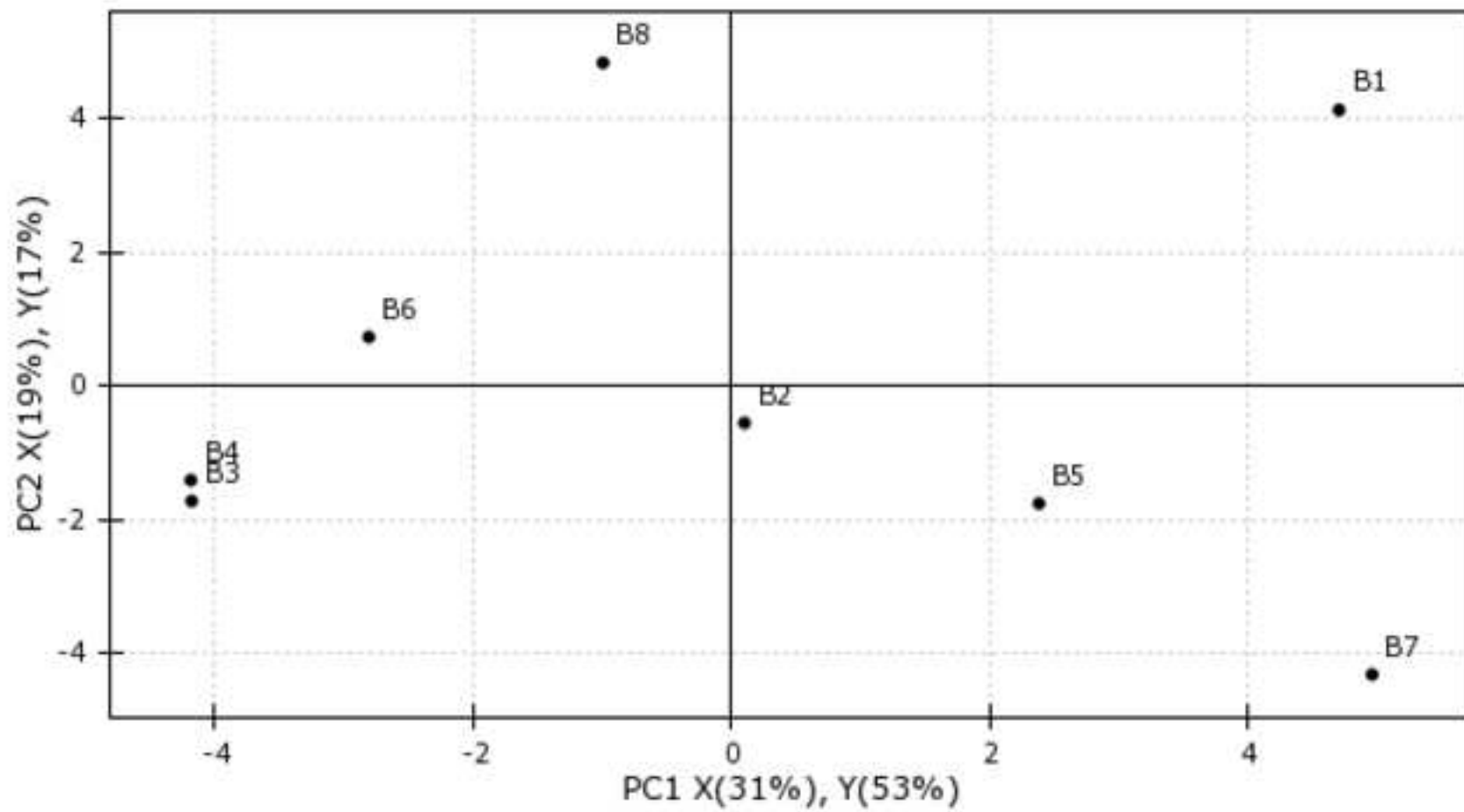


Figure 2b

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Correlation loadings

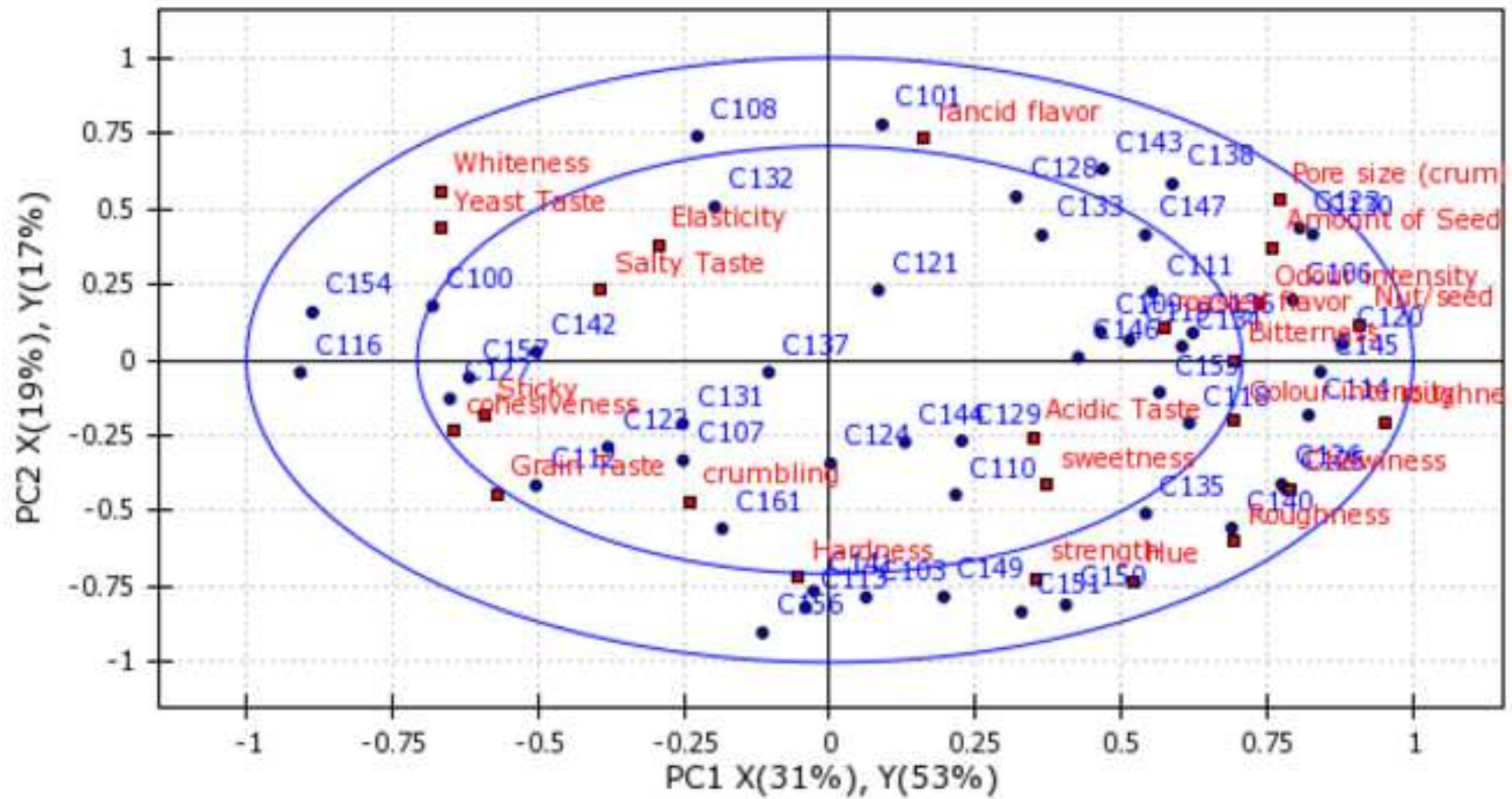


Figure 3
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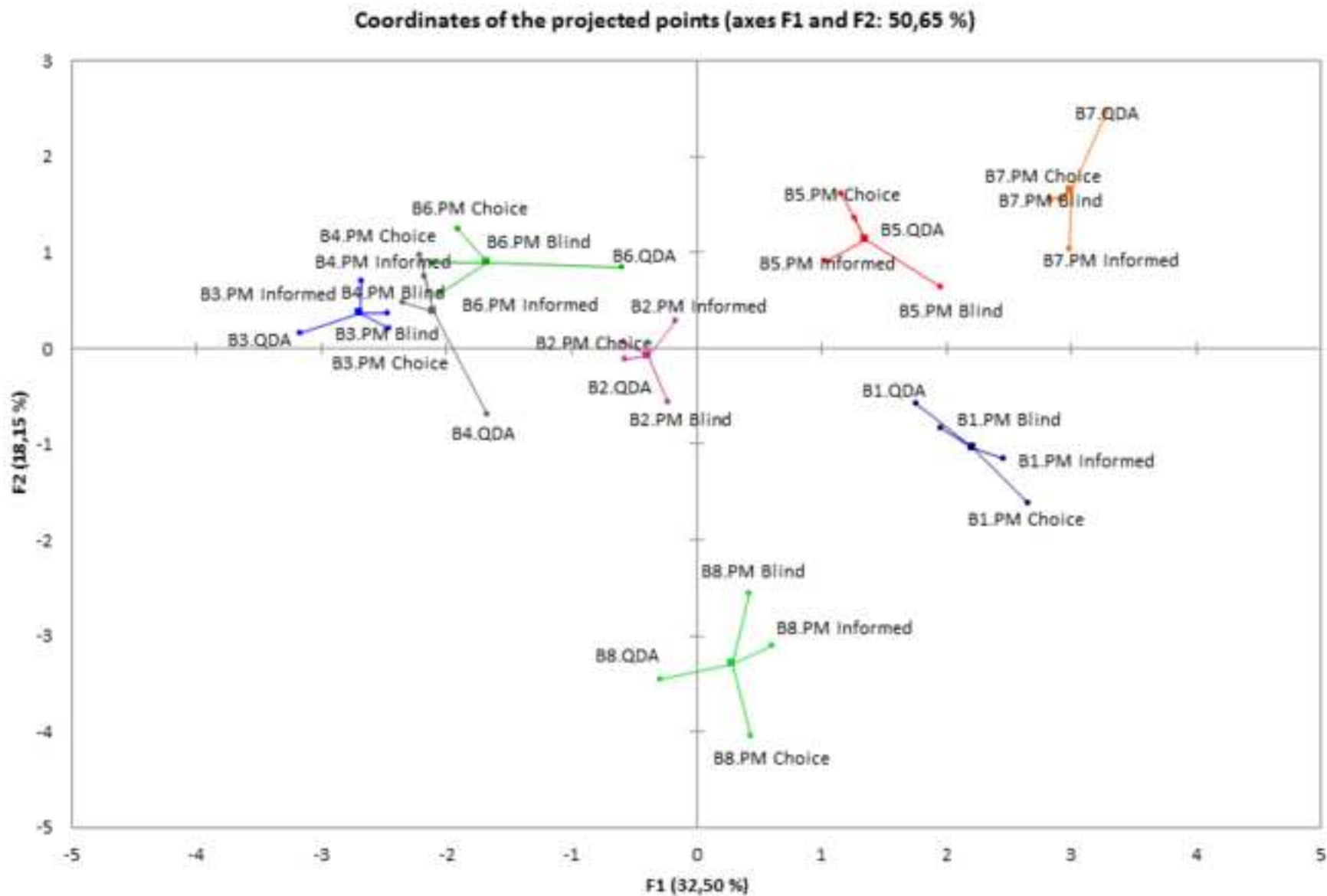


Figure 4
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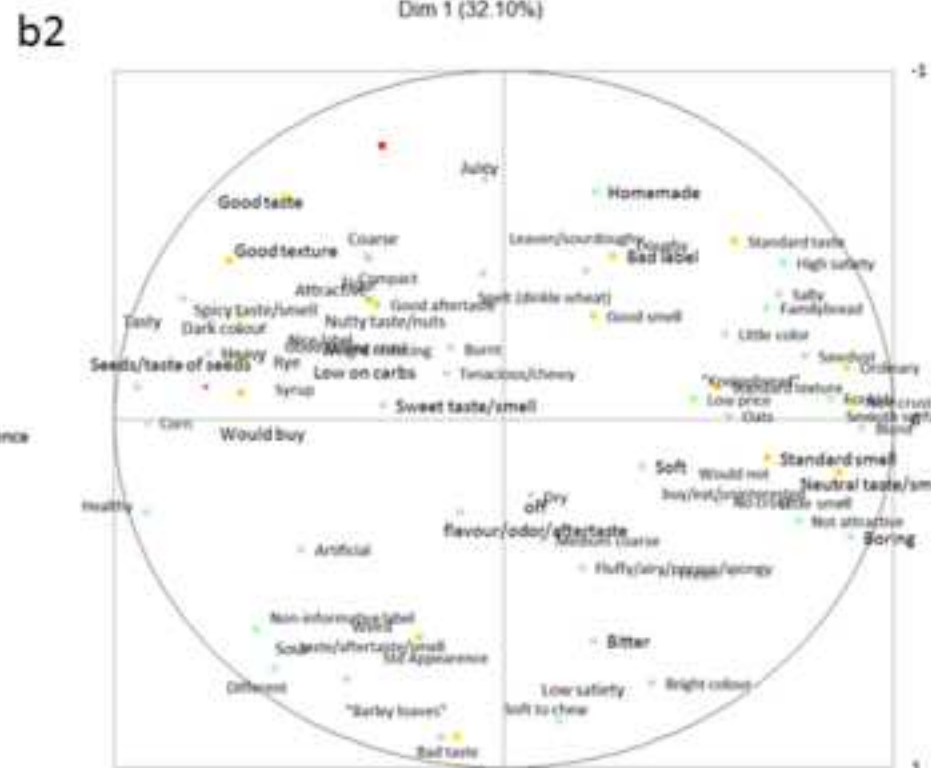
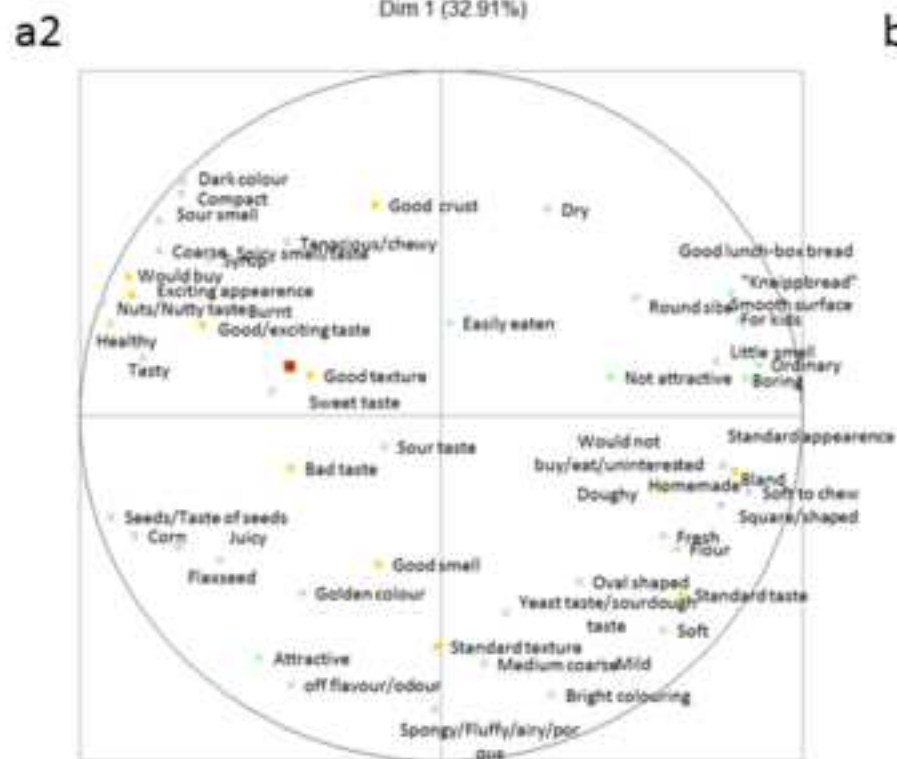
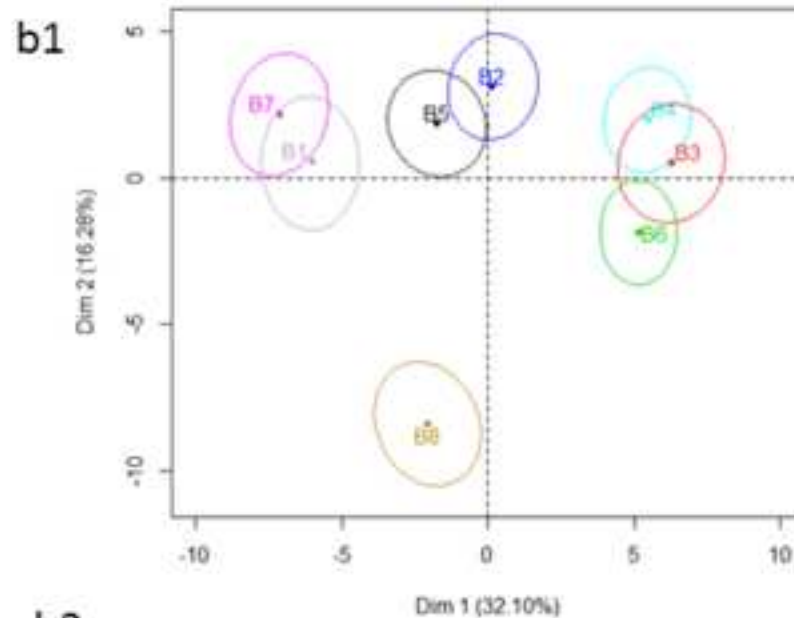
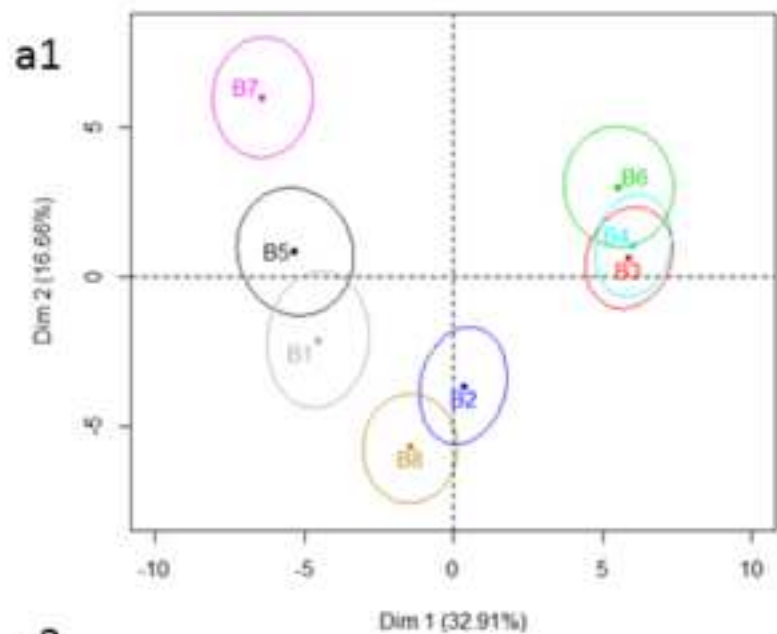


Figure 5
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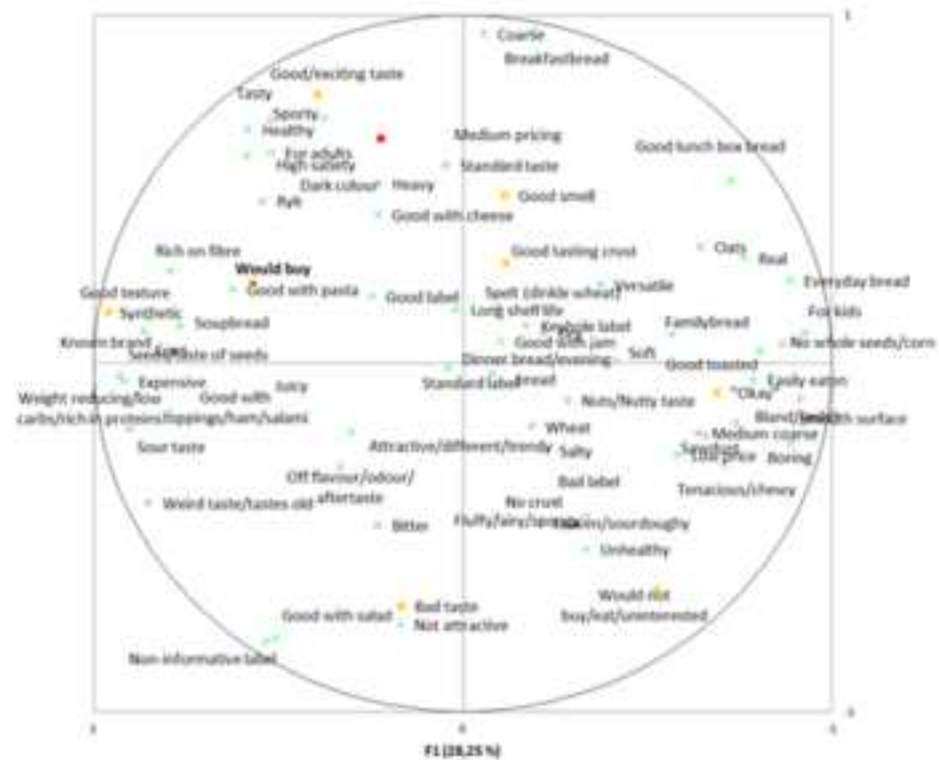
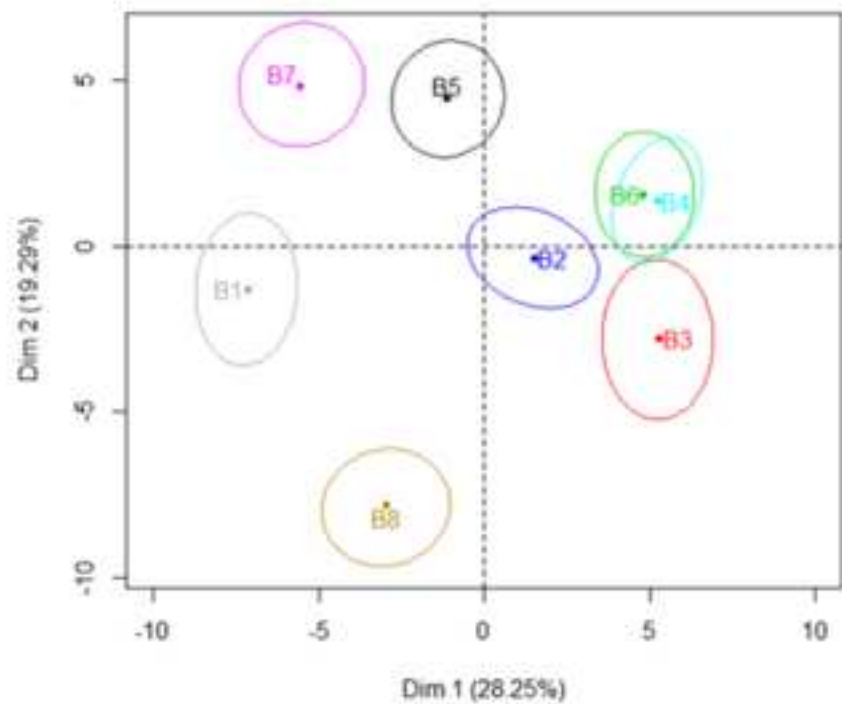


Figure 6
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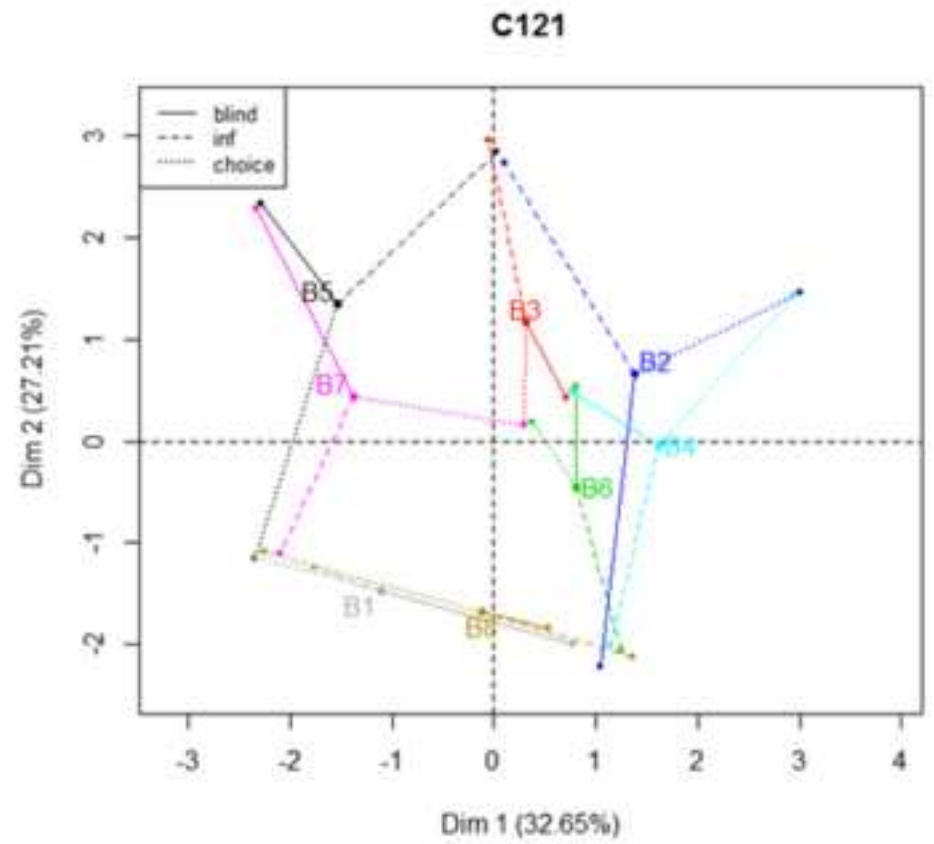
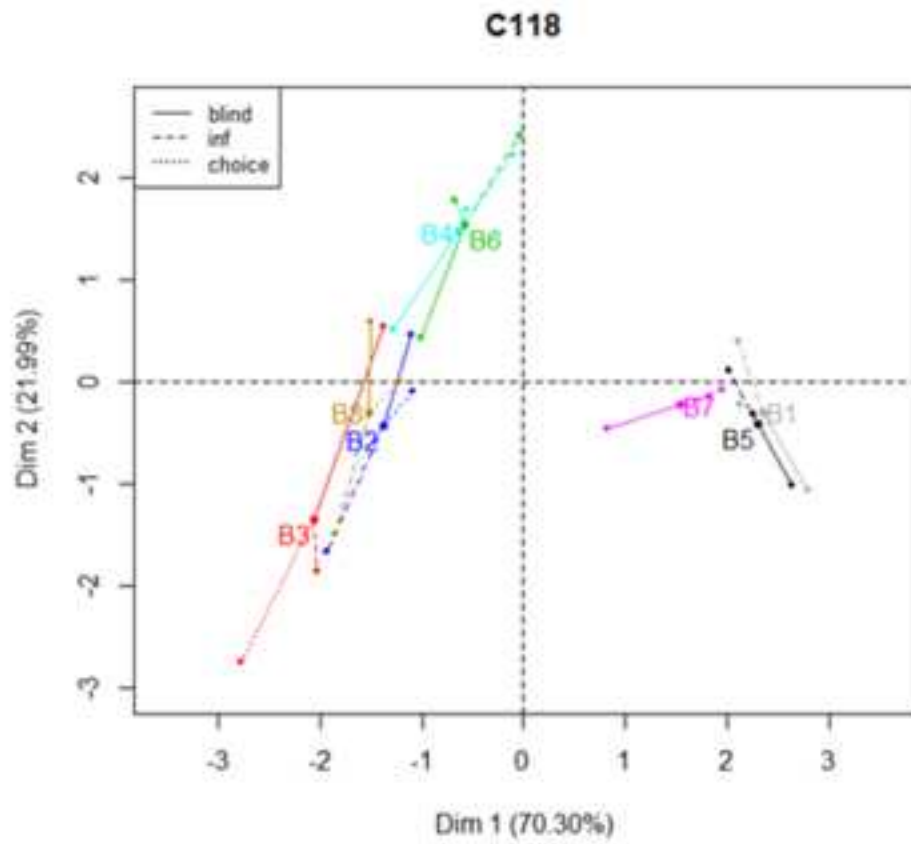


Figure 7
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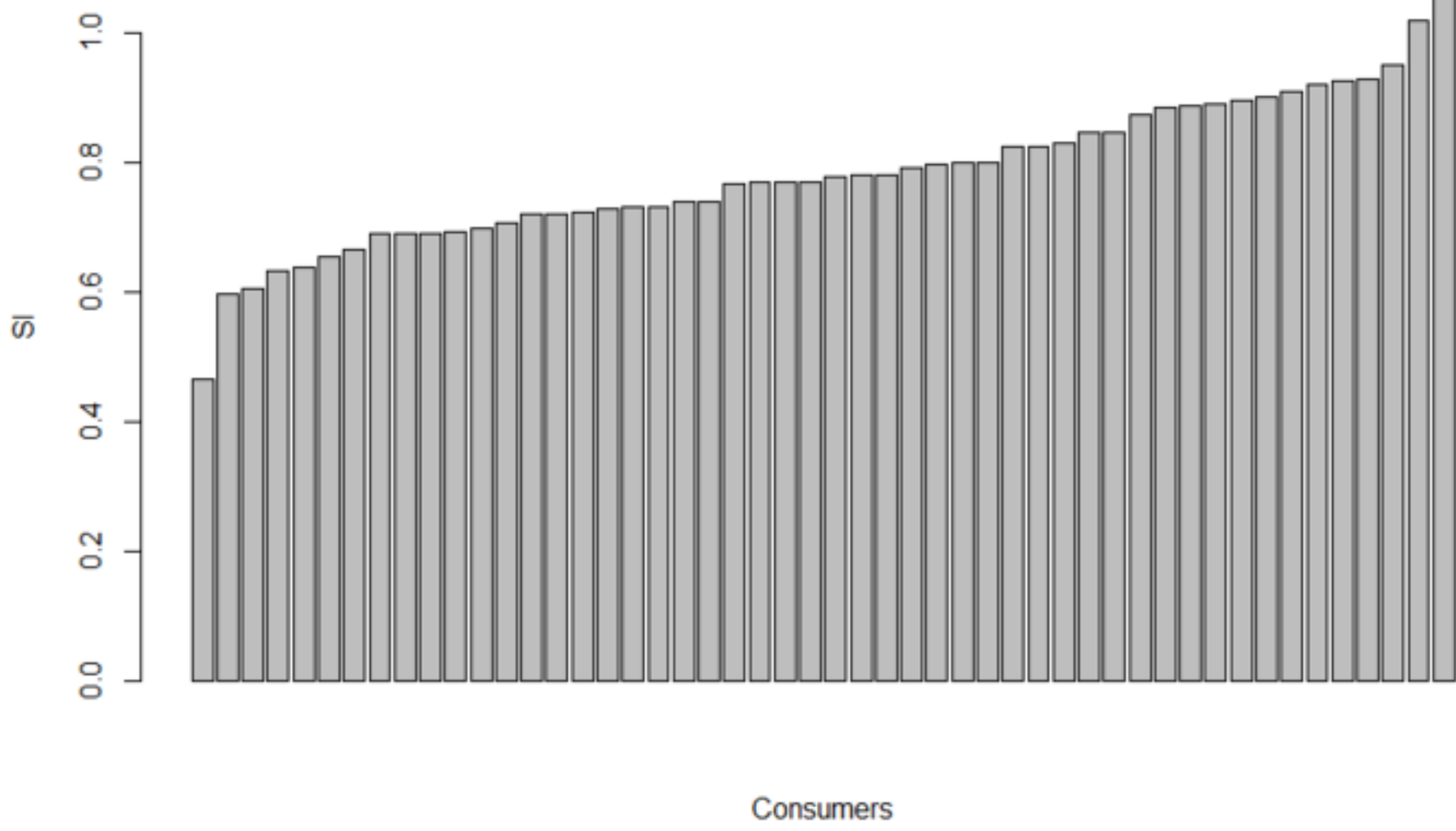


Table 1.- Bread samples included in the research

Sample	Type of bread	Half-Coarse 25-50% whole grain	Coarse 50-75% whole grain	Extra coarse 75-100% whole grain	Keyhole label	Claims
B1	Wholegrain	x				Balance. Protein rich, less carbohydrates, “smart-carbo”, high fiber, beneficial fats, stable blood sugar
B2	Dinkle Wholegrain		x		x	
B3	Wholegrain		x		x	
B4	Wholegrain with oats			x	x	
B5	Wholegrain with oats and rye			x	x	Sport bread. Gold recipe. The taste of success is unbeatable
B6	Oats			x	x	High fiber
B7	Rye			x	x	Healthy and well, good for the body. Long lasting satiety, health & taste winner. High fiber
B8	Barley			x	x	B-glucans, lower cholesterol, Long lasting satiety, norwegian grain

Table 2.- Mean OL ratings and Fisher LSD for the whole group and the two clusters

Bread Sample	OL all consumers (n=50)	OL Cluster 1 (n=20)	OL Cluster 2 (n=25)
B1	5.6 ^{a,b}	4.5 ^{a,b}	6.8 ^a
B2	5.8 ^a	5.3 ^a	6.2 ^{a,b,c}
B3	4.7 ^{c,d}	5.0 ^a	4.4 ^d
B4	4.9 ^{b,c}	5.4 ^a	4.4 ^d
B5	5.9 ^a	5.0 ^a	6.7 ^a
B6	4.9 ^{b,c}	4.8 ^{a,b}	5.1 ^{b,c,d}
B7	5.1 ^{a,b,c}	4.0 ^{a,b}	6.3 ^{a,b}
B8	4.1 ^d	3.2 ^b	4.9 ^{c,d}

