

1 Title: Panelists' performances and strategies in paper based and computer based projective  
2 mapping

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4 Running title: computer and paper based projective mapping

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15

16 Abstract:

17 Projective Mapping has recently attracted a lot of attention and the main sensory data  
18 acquisition software packages have developed interfaces to collect projective mapping data.  
19 However, the comparison between paper and computer based projective mapping has never  
20 been reported. The objectives of this research were to 1) compare the consensus maps and  
21 panelists' performances for paper and computer based projective mapping and 2) analyze the  
22 panelists' strategies while performing either tasks. In the first part of the study, 32 panelists  
23 were asked to perform both paper and computer based projective mapping on 8 beer samples.  
24 In a second part of the study, 10 panelists were asked to repeat the tasks whilst “thinking  
25 aloud” their strategy. There was no significant difference in panelists' performance as  
26 assessed by the People Performance Index (PPI) between the paper and computer tasks. The  
27 consensus maps obtained were similar with respect to sample groupings, RV coefficients and  
28 variation explained by the first 2 dimensions. Individual panelists adopted similar strategies  
29 on paper and computer but strategies differed greatly between panelists.

30 Practical applications:

31 The results reported here will help panel leaders making informed decisions with respect to  
32 support choice when designing projective mapping tests. Additionally, an insight into the  
33 diversity of panelists' mapping strategies is provided which may inform further research and  
34 discussion into the most appropriate instructions given to panelists and/or type of panel used.

35 Key words: Projective Mapping, Napping, sensory, People Performance Index, Think Aloud,  
36 MFA.

37

38 1. Introduction:

39 Projective Mapping is a relatively recent descriptive technique (Risvik *et al.* 1994; Risvik *et*  
40 *al.* 1997) which has attracted a lot of attention due to its relative ease of use and cost  
41 effectiveness compared to the more traditional descriptive methods such as Quantitative  
42 Descriptive Analysis (QDA). As a result, a number of contributions have focused on  
43 evaluating the performance of projective mapping and its limitations against other rapid  
44 descriptive methods (Ares *et al.* 2010; Nestrud and Lawless 2010) or traditional descriptive  
45 analysis (Kennedy and Heymann 2009; Mielby *et al.* 2014; Moussaoui and Varela 2010). The  
46 consensus is that projective mapping is well suited to gathering quick, preliminary descriptive  
47 information on samples which present a reasonable degree of dissimilarity and that it  
48 compares well with other rapid methods (Mielby *et al.* 2014; Varela and Ares 2012).  
49 Identified strengths of projective mapping are its holistic nature and versatility with respect to  
50 the type of panel (consumer vs. trained). Since judges are not given any instructions relating  
51 to the discrimination criteria to use in order to build their maps, projective mapping has often  
52 been described as a holistic method (Dehlholm *et al.* 2012; Varela and Ares 2012). This  
53 differs in nature to other descriptive methods, notably QDA, in which panelists analytically  
54 assess attributes separately (Lawless and Heymann 2010). This difference between the  
55 techniques may be reflected in the type of panel used to carry out projective mapping and a  
56 number of studies have focused on whether consumers could be used to generate equivalent  
57 data as trained panelists. Some have concluded this was the case (Albert *et al.* 2011), and  
58 others have found that trained panelists performed better (Barcenas *et al.* 2004). Despite the  
59 assumption that judges approach the task holistically, there is, to date, no real insight into the  
60 strategies which panelists adopt to perform projective mapping.

61 As limitations go, it is accepted that projective mapping does not provide the same richness  
62 of descriptive information as QDA and notably, there are not any average scores which can

63 be compared across samples for any attribute (Valentin *et al.* 2012), prompting some to  
64 question their "actionability" (Moskowitz 2002) .

65 Despite these well documented limitations, projective mapping has been applied and  
66 validated with an ever growing range of food products such as fresh strawberries (Vicente *et*  
67 *al.* 2014); mortadellas (Santos *et al.* 2013); potato purees (Jimenez *et al.* 2013) and high  
68 alcohol beverages (Louw *et al.* 2014) to cite only the most recent examples. In this context  
69 of fast growth, it is not surprising that all the major sensory data acquisition software  
70 packages have now developed interfaces to collect projective mapping data directly on  
71 screen, by-passing thus the elaboration of a map using physical products placed on a large flat  
72 surface. However, to date, no study has reported whether the results obtained from the  
73 traditional paper based projective mapping agreed with those obtained via computer screens.  
74 Comparison between pen-and-paper and online data acquisition methods are well  
75 documented in other fields such as social sciences (Campos *et al.* 2011; Díaz de Rada and  
76 Domínguez-Álvarez 2014; Gravlee *et al.* 2013). Overall, there appears to be a good  
77 agreement between the 2 methods, with subtle differences observed in terms of item response  
78 rates and expense of qualitative data generated from open ended questions (Díaz de Rada and  
79 Domínguez-Álvarez 2014). However, there are major differences between surveys and  
80 sensory analysis, namely the controlled conditions in which the data is acquired (sensory  
81 booths) and the fact that panelists are required to taste food products as part of the task and  
82 few sensory studies have looked into the comparability of paper and computer acquisition  
83 methods. A descriptive sensory study concluded that substituting paper ballots for computer  
84 ballots did not significantly alter experimental results (Swaney-Stueve and Heymann 2002).  
85 However, the transferability of these findings to projective mapping is yet to be  
86 demonstrated.

87 The objectives of this research were twofold: to compare the consensus maps for paper and  
88 computer based projective mapping as well as to analyze the panelists' strategies while  
89 performing either task.

90

## 91 2. Materials and Methods:

92 The aim of the first study was to compare the maps obtained on paper and on computer.  
93 Thirty-two consumers were asked to perform both paper and computer based projective  
94 mapping on 8 samples of beer (6 different samples and 2 duplicates). The aim of the second  
95 study was not to compare the projective mapping results for both tasks (first study) but to  
96 investigate the strategies adopted by the panelists. Ten panelists were asked to perform the  
97 same tasks once more while describing their strategies. In a food context, asking panelists to  
98 “think aloud” as they perform a task to understand their working has been insightfully used  
99 elsewhere to investigate emotion reporting (Jaeger *et al.* 2013) but also to obtain an insight  
100 into participants’ cognitive strategies when presented with different recall aids to estimate  
101 portion sizes (Chambers *et al.* 2000). The study set-up was deliberately selected to explore  
102 the relative performance of paper and computer based projective mapping in the most  
103 challenging and relevant to routine data acquisition conditions: consumers, rather than a  
104 trained panel, were used and a complex product (beer) was selected as this has been shown to  
105 impact on results (Louw *et al.* 2014).

106

### 107 2.1. Panellists:

108 Thirty-two regular (at least once every 2 months) beer drinkers (20 males) aged 20 to 60 were  
109 recruited via flyers and word of mouth to take part in the first part of the study. They were  
110 composed of 19 academic staff, 9 technical/manual workers and 4 students. The number of

111 untrained panelists / consumers used in studies comparing projective mapping to other  
112 techniques ranges between 8 and 30 panelists and is typically between 12 to 24 panelists (for  
113 a detailed review of number of panelists in projective mapping studies, see Table 1 of Hopfer  
114 and Heymann 2013). Ten of those panelists (6 males) aged 20 to 50 agreed to come back for  
115 the second part of the study for an in-depth investigation of their strategies.

## 116 2.2.Samples:

117 An initial screening of the samples ensured a reasonable homogeneity of the samples. Three  
118 alcohol levels were selected: alcohol free (Beck's blue containing no more than 0.05% ABV  
119 by Beck's and Erdinger Alkoholfrei by Erdinger Weißbräu), light beers (Beck's premium  
120 light 2.3% ABV by Beck's and Bière Blonde 2.6% ABV by Brasserie) and regular beers  
121 (Beck's 4.8% ABV by Beck's and Foster Gold 4.8% ABV by Foster). Two blind duplicates  
122 were included to assess judge's ability to perform the task and discriminate between samples.  
123 In order to minimize the amount of alcohol ingested by the panelists, the two alcohol free  
124 beers were selected as the duplicate samples. Forty ml of fridge cold (4°) samples were  
125 presented in small transparent plastic gallipots simultaneously to the panelist. The order in  
126 which the samples were arranged on the trays differed between panelists and was based on  
127 William's Latin square design.

## 128 2.3.Studies:

### 129 2.3.1. First study:

130 The panelists were randomly allocated to either perform the paper or computer projective  
131 mapping task during their first session and came back to perform the other task at a later time,  
132 typically one week later. In line with the procedure described in Dehlholm *et al.* (2012), the  
133 panelists, who had never performed a projective mapping task before, attended a 10 minutes

134 instruction session prior to both tasks. For the paper task, panelists were shown an example of  
135 a paper map acquired with tomato soup samples. For the computer task, panelists were  
136 required to build their maps on the computer screen within the space provided to that effect.  
137 They were shown, on a large projection screen, how to move the samples within that space  
138 and how to record attributes for each sample on electronic sample tags. Panelists attended  
139 both sets of instruction sessions regardless of which task they performed first. The  
140 instructions provided in the booths were the same for both tasks: "Please evaluate the  
141 samples in front of you from left to right and place them on the provided space according to  
142 how similar or dissimilar they are for you. The more similar the samples are, the closer they  
143 should be positioned to each other, the more dissimilar they are the further apart they should  
144 be positioned" (Hopfer and Heymann 2013).

145 After completing both tasks, panelists were asked which task they had felt most comfortable  
146 with and why.

#### 147 2.3.2. Second study:

148 Ten panelists aged 20 to 50 (6 males, 6 academic staff, 3 technical staff and 1 student) agreed  
149 to come back and take part in the second study which involved performing both the paper and  
150 computer projective mapping whilst thinking aloud their strategies. The panelists, who  
151 already had experience of both supports, were randomly allocated to start either with the  
152 paper or computer task and were reminded of the general instructions for each task.  
153 Additionally, they were asked to think aloud their strategies as they carried out the tasks and  
154 were recorded using a SONY IC Recorder (ICD-PX312/PX312F).

#### 155 2.4.Support:

156 For the paper task, panelists were provided with sheets of paper measuring 60 cm x 40 cm.  
157 For the computer task, panelists were not provided with any paper and performed their maps  
158 directly on the computer screen available on the booth. The computer screens were 24.6 cm x  
159 18.5 cm and the actual map space dimensions were 16.0 cm x 10.6 cm. While the supports  
160 dimensions varied greatly, it was important to compare the methods as they would be applied  
161 by panel leaders who would not dispose in their booths of computer screens of equivalent  
162 dimensions as the paper maps most commonly used in projective mapping (60 cm x 40 cm).  
  
163 For the paper maps, each sample coordinate was measured from the bottom left corner of the  
164 map and reported in Excel (Microsoft, Seattle, US) along with the attributes generated by the  
165 panelists. For the computer maps, the data was acquired using Compusense (Guelph, Canada)  
166 and the coordinates of the computer based maps were exported from Compusense into Excel  
167 along with the attributes generated by the panelists for each sample.

## 168 2.5. Data analysis:

### 169 2.5.1. People Performance Index:

170 The People Performance Index (PPI) which is the ratio between the distance separating 2  
171 duplicates over the greatest distance separating any 2 samples on the map was calculated as  
172 reported in Hopfer and Heymann (2013). A factorial repeated measures ANOVA (repeated  
173 measure: panelist; factors: duplicate pair and support) was performed using SPSS v21 (IBM  
174 Corporation, Armonk, NY) to test for significant differences in PPIs.

175 Additionally, based on individual map examination, criteria to assess panelists' performance  
176 based on their PPIs were introduced as such:  $PPI \leq 0.20$  excellent;  $0.20 < PPI \leq 0.30$  good;  
177  $0.30 < PPI \leq 0.40$  fair;  $0.40 < PPI \leq 0.50$  poor;  $0.50 < PPI$  inadequate.

### 178 2.5.2. Product coordinates and attributes count:



179 Multiple Factor Analysis (MFA) was introduced to deal with data tables of different natures  
180 by, in essence, performing a PCA on each subset of data and superimposing them (Pagès and  
181 Husson 2001). In this respect, it has proved highly suitable to analyze projective mapping  
182 data where product coordinates and attribute counts can be analyzed simultaneously. The  
183 paper and computer based projective mapping data were analyzed by MFA (MFA, Husson et  
184 al. 2014) in R (R core team 2013) using FactoMineR (Lê *et al.* 2008). A Hierarchical Cluster  
185 Analysis (HPCP, Husson et al. 2014) was performed on the first 5 dimensions of the MFA  
186 results. Each individual map was considered as a group and RV coefficients were computed  
187 (MFA using FactoMineR) to evaluate the degree of agreement between individual maps as  
188 well as individual maps and overall configuration (Robert and Escoufier 1976). Synonyms of  
189 attributes used to describe the samples were pooled together (example: "pale" and "light  
190 colour") and attributes cited only once were discarded as reported elsewhere (Ares *et al.*  
191 2010; Albert *et al.* 2011). For each modality (paper and computer), the attribute frequency  
192 counts across all assessors were collated as a separate group in the same data structure as that  
193 described by Nestrud and Lawless (2008); Moussaoui and Varela (2010) and Pagès (2005).  
194 Hierarchical Multiple Factor Analysis (HMFA) was introduced to take into account the  
195 hierarchical nature of some data sets (Le Dien and Pagès 2003) and has successfully been  
196 applied to the comparison of sensory methods (Perrin *et al.* 2008; Ares *et al.* 2010) or  
197 replicates (Kennedy 2010). It was therefore used to represent the combined product map from  
198 the paper and computer projective mapping (1<sup>st</sup> level) which were themselves composed of 2  
199 groups: map coordinates and attribute frequency counts.

### 200 2.5.3. Think Aloud Task:

201 The panelists' strategy audio files were analyzed for content and 4 dimensions were derived  
202 from the analysis in order to fully characterize the mapping strategies adopted. At the start of  
203 the task, panelists were found to differ in their **early attention focus** (building the map or

204 generating attributes); moreover some panelists compared samples for overall  
205 similarities/differences while others focused on specific attributes to build their maps. This  
206 lead to the generation of a **holistic vs attribute driven approach** dimension. Some panelists  
207 attributed meanings to their axis and this was recorded in a 3<sup>rd</sup> dimension (**axis meaning**) to  
208 investigate whether different panelists used different attributes to discriminate between  
209 samples. Finally, which criteria were used to place the samples on the map (grouping similar  
210 samples or placing different samples apart) was recorded in the **grouping strategy**  
211 dimension. Panelist's strategies were assessed against those 4 dimensions for each modality.

212

213 3. Results:

214 3.1. Panelists' performance

215 The presentation of 2 pairs of duplicate samples for both paper and computer based maps  
216 meant that 4 PPIs were generated by panelist. The PPIs ranged from 0.04 to 1.00 and  
217 averaged 0.30 and 0.39 on the paper and 0.31 and 0.35 on the computer for duplicate pairs 1  
218 and 2 respectively. For each task, panelists were excluded from the final analysis if both PPIs  
219 were greater than 0.40 (poor) or the average of both PPIs was greater than 0.50 (inadequate)  
220 as this was taken as an indication that the panelist had difficulties either with the task or the  
221 type of sample. Twenty three and 24 panelists were included respectively in the paper and  
222 computer analysis.

223 Twenty panelists out of 32 stated that they were more comfortable with the computer task;  
224 overwhelmingly citing being able to move the samples around the screen map on re-taste as  
225 the main reason for this (although this flexibility was cited as the reason for preferring the  
226 paper support by one panelist who felt it was too easy to change her mind). The judges who  
227 were more comfortable performing the task on paper (10 out of 32) often cited the same

228 reason: greater flexibility to move samples around and use the whole space but also cited  
229 being able to draw relationships between samples/attributes (using arrows for example). Two  
230 panelists out of 32 stated being equally comfortable performing either. Overall, the majority  
231 of the panelists was more comfortable using the computer to perform the task however; this  
232 did not translate into a significantly better performance as assessed by PPI and there was no  
233 significant difference in performance with respect to support type ( $p = 0.744$ ) or duplicate  
234 pair ( $p = 0.105$ ).

### 235 3.2. Consensus maps

#### 236 3.2.1. Comparison between paper and computer based projective mapping

237 A HMFA was performed on the paper and computer dataset. The samples coordinates and  
238 attribute frequency count represented one level of hierarchy and acquisition method  
239 (paper/computer) represented another. Figure 1 presents the overall product map with the  
240 superimposed partial clouds associated with the 2 tasks and Figure 2 presents the relationship  
241 of the groups to the first two dimensions.

242 Figures 1 and 2 thereabout

243 Both sets of duplicate samples came out grouped together. The space was defined by a  
244 triangle which extremities were represented by the Erdinger and Beck's blue samples (clearly  
245 opposed on dimension 1) and the Brasserie Blonde and beck's light (opposed to the others on  
246 dimension 2). The partial clouds representing both acquisition methods remained close to the  
247 samples barycenter indicating a good level of agreement between the methods; this was  
248 further supported by the proximity of the groups with respect to their contribution to  
249 dimension 1 and 2 (variation 61.4%, Figure 2). However, while this representation pointed to  
250 a good agreement between the paper and computer tasks, it did not give any indication of

251 agreement between individual maps and each acquisition method was studied separately to  
252 this effect.

253 Figures 3 and 4 present the consensus maps obtained respectively from the paper and  
254 computer based projective mapping exercises.

255 Figures 3 and 4 thereabout

256 There was an overall excellent agreement between the paper and computer generated  
257 consensus maps. The first 2 dimensions represented respectively 61.7% and 59.5% of the  
258 variation for the paper and computer projective mapping tasks. The samples groupings were  
259 very similar for both modalities as evidenced by identical clusters (Figures 3 and 4).  
260 Duplicate samples were grouped together while the 2 light beers were grouped together and  
261 the 2 strong beers formed the last cluster. Dimension 1 opposed the Erdinger samples to the  
262 Beck's blue samples while dimension 2 opposed the light beers (Beck's light and Brasserie  
263 Blond) to the other samples. Beck's and Foster Gold were found towards the center of the  
264 maps.

265 The average number of attributes generated per panelist and per sample was slightly greater  
266 for the computer task (4.2) than for the paper task (3.6). Grouping synonyms and removing  
267 the attributes cited only once resulted in the generation of respectively 36 and 31 different  
268 attributes for the paper and computer tasks. The attributes significantly correlated to the first  
269 two dimensions are presented in Table 1.

270 Table 1 thereabout

271 A strong level of agreement in sample description/attribute generation was observed between  
272 the paper and computer tasks with 8 common attributes for dimension 1 (5 positively  
273 correlated and 3 negatively correlated) and 1 common attribute (bland, negatively correlated)

274 for dimension 2. Anecdotally, panelists did not generate attributes related to alcohol content  
275 or strength and informal feedback indicated that they had not guessed that some beers were  
276 alcohol free.

### 277 3.2.2. Panelists' comparison

278 Reasonably good agreements were observed between the individual maps and the consensus  
279 maps with RV coefficients averaging 0.69 (range 0.45 to 0.93) for the paper MFA and 0.63  
280 (range 0.30 to 0.93) for the computer MFA. RV coefficients between individual maps ranged  
281 from 0.06 to 0.92 (average 0.44) and 0.01 and 0.88 (average 0.35) for respectively the paper  
282 and computer projective mapping tasks. While these values are in line with those reported  
283 elsewhere (Hopfer and Heymann 2013), they are indicative of poor agreements between  
284 some of the individual maps. This disagreement is unlikely to stem from poor quality maps as  
285 only maps meeting the PPI criteria outlined in section 3.1. and deemed of good quality were  
286 included in the final analysis. In order to understand the origin of the poor agreement  
287 observed between some individual maps, 10 panelists were asked to come back for a second  
288 session in which they were required to “think aloud” their strategies whilst performing the  
289 tasks. Content analysis of the recordings identified 4 dimensions to the panelists' mapping  
290 strategies. The breakdown of the panelists' strategies into these 4 dimensions is presented in  
291 Table 2.

292 Table 2 thereabout

293 The strategies adopted by panelists from task to task proved remarkably stable on all 4  
294 strategy dimensions. In this respect, a change of support did not induce a major shift in  
295 panelists' strategy but often resulted in an adaptation of the same strategy. For example, on  
296 first tasting, panelist 3 wrote the samples attributes in one corner of the paper map or on the  
297 electronic tags. But different panelists adopted vastly different strategies ranging from purely

298 holistic with no articulated meaning associated with the axis to attribute-led approaches in  
299 which the panelist attributed meanings to the axis. Even within these two approaches (holistic  
300 vs. attribute-led), there existed considerable differences in the map construction for the  
301 holistic approach with some panelists clustering similar samples together (panelist 1), others  
302 focusing on greatest differences (panelist 5) and yet another clustering samples by perceived  
303 “class” of samples (panelist 8: traditional beers / low quality). For the attribute-led approach,  
304 the choice of attributes around which the map was built differed with criteria based on three  
305 different modalities: appearance, taste and texture. It is interesting to notice that while none  
306 of the panelists explicitly used smell to label their axis, a number of attributes related to  
307 aroma compounds were significantly correlated with the first two dimensions on the maps,  
308 such as flowery, fruity, caramel and honey. This is consistent with the approach used by  
309 panelist 6 who defined axis meanings (bitterness and thickness) but fine-tuned the map using  
310 other attributes (smell). There was no difference between the average PPI values obtained  
311 using the holistic approach (average: 0.23) and attribute-led approach (average: 0.23).

312

#### 313 4. Discussion:

314 Overall, despite the fact that a majority of panelists were more comfortable performing  
315 projective mapping on the computer, which may be a reflection of the panelists' occupations,  
316 the type of support (paper/computer) did not impact on panelists' performance as assessed by  
317 the PPI; nor did it impact on the final map results with very similar consensus maps generated  
318 in terms of sample grouping and opposition between samples. In this respect, it could be  
319 argued that the paper and computer maps generated did not differ more than replicates of the  
320 same task, indeed studies specifically investigating projective mapping repeatability showed  
321 that overall similarities and dissimilarities were conserved despite somewhat different

322 consensus maps (Hopfer and Heymann 2013) and/or poor agreements between individual  
323 panelist's replicates (Kennedy 2010). Whilst there is surprisingly little literature on the  
324 subject of paper vs. computer in the field of sensory science, it has often been reported that  
325 pen-and-paper and online data acquisition methods yield similar results in other disciplines  
326 (Campos *et al.* 2011; Díaz de Rada and Domínguez-Álvarez 2014; Gravlee *et al.* 2013;  
327 Swaney-Stueve and Heymann 2002). The subtle differences reported surrounded item  
328 response rate and expense of answers on open ended questions, which may be compared to  
329 the number of attributes generated in projective mapping. In this respect, the same trend was  
330 observed in this study whereby the average number of attributes generated per sample and per  
331 panelist was slightly higher on the computer than on paper, however, this did not result in  
332 richer sample descriptions as slightly more different attributes were generated on paper. A  
333 similar observation was reported when comparing paper and computer based hard laddering  
334 techniques (Russell *et al.* 2004): participants, who were able to review previous answers on  
335 the paper, generated new links between levels while they re-used more often existing links on  
336 the computer. In the computer version of projective mapping, panelists could easily select  
337 attributes which they had already typed to describe another sample and this may have  
338 facilitated their selection and discouraged the generation of new attributes, resulting in a  
339 higher average number of attributes per sample and panelist but an overall lower number of  
340 different attributes used to characterize the sample set. However, the differences remained  
341 small and the overall trend was that of a good agreement between the techniques.

342 The fact that a small percentage of panelists struggle with projective mapping is well  
343 documented (Pagès 2005; Veinand *et al.* 2011) with panelists rating projective mapping as  
344 more difficult than techniques based on the evaluation of sensory characteristics (Ares *et al.*  
345 2011). In line with this, some poor performances on the people performance index were  
346 observed and results from panelists who failed to correctly identify duplicates were not

347 included in the final analysis. Despite this, RV coefficients demonstrated a range of  
348 agreement levels between individual maps as observed elsewhere (Hopfer and Heymann  
349 2013). This may partly be explained by the vastly different strategies adopted by panelists  
350 irrespective of the support used. Although the number of panelists used in the second part of  
351 the study is relatively small, the study did not aim to report all possible strategies adopted and  
352 there is sufficient evidence that considerable differences in how panelists having received the  
353 same instructions approach the task, exist. While self-reported strategies in projective  
354 mapping have never been documented before, different cognitive strategies which appeared  
355 unrelated to spatial or verbal abilities have been evidenced in conceptual mapping (Hilbert  
356 and Renkl 2008), In projective mapping, different separation criteria and map structures were  
357 reported elsewhere using a close examination of the maps generated (Hopfer and Heymann  
358 2013). Our findings extend and confirm these observations. This sheds a new light on  
359 projective mapping as a task which has up until now frequently been described as a holistic  
360 method (Dehlholm *et al.* 2012; Varela and Ares 2012) as opposed to an attribute-driven (or  
361 reductionist) one. It is clear from this data that while the holistic dimension of the task is  
362 represented in the fact that panelists are free to select the attributes which they use to  
363 discriminate between samples; some panelists spontaneously adopt a reductionist approach.  
364 This may explain the success of partial napping, in which panelists are required to build  
365 different maps for each modality with greater RV coefficients reported for replicates within  
366 each modality than for global napping (Louw *et al.* 2013). This could be attributed to a lower  
367 number of possible attributes against which operating the discrimination in partial napping.  
368 This may be taken as an indication that more prescriptive instructions may improve  
369 performance, however, no trend was observed with respect to panelists' strategy and  
370 performance on PPI. The range of strategies adopted by consumers may partly explain why a  
371 relatively high number of consumers compared to current practices in the field has recently



372 been advocated to ensure map stability; although this was estimated using a conservative RV  
373 coefficient criteria and it was noted that the number of consumers required to reach stability  
374 decreased with increasing levels of difference between the samples (Vidal *et al.* 2014).  
375 Introducing blind duplicates to remove the judges experiencing difficulties with the task or  
376 product range may also increase reliability and decrease the number of consumers required.

377

## 378 5. Conclusion:

379 The majority of panelists reported being more comfortable performing the task on computer;  
380 however, this did not impact on panelists' performance which was not significantly different  
381 between the paper and computer tasks and there was a high level of agreement between the  
382 paper and computer consensus maps. Panelists adopted similar strategies to perform either  
383 task, but those differed drastically between panelists. In this respect, the limitations of  
384 computer based projective mapping are the same as those documented for paper based  
385 projective mapping. It is recommended that blind duplicates are included in the sample set. It  
386 is likely that the panelists used in this study were reasonably computer literate and not fully  
387 representative of consumers selected from a wider range of occupations. These results should  
388 therefore be interpreted with caution and may not be generalized to populations with low  
389 degrees of computer literacy.

390 Further work should investigate strategies adopted by trained panels as they may approach  
391 the task in a more analytical way and may display greater consensus around the attributes  
392 selected to discriminate between samples.

393

## 394 6. Declaration of interest:

395 The authors do not have any conflict of interest to declare.

396

397 7. List of references:

398 ALBERT, A., VARELA, P., SALVADOR, A., HOUGH, G. and FISZMAN, S. 2011.  
399 Overcoming the issues in the sensory description of hot served food with a complex texture.  
400 Application of QDA, flash profiling and projective mapping using panels with different  
401 degrees of training. *Food Qual. Pref.* 22, 463-473

402 ARES, G., DELIZA, R., BARREIRO, C., GIMÉNEZ, A. and GÁMBARO, A. 2010.  
403 Comparison of two sensory profiling techniques based on consumer perception. *Food Qual.*  
404 *Pref.* 21, 417-426

405 ARES, G., VARELA, P., RADO, G. and GIMÉNEZ, A. 2011. Are consumer profiling  
406 techniques equivalent for some product categories ? The case of orange-flavoured powdered  
407 drinks. *Int. J. Food Sci. Technol.* 46, 1600-1608

408 BARCENAS, P., PÉREZ ELORTONDO, F. J. and ALBISU, M. 2004. Projective mapping in  
409 sensory analysis of ewes milk cheeses: A study on consumers and trained panel performance.  
410 *Food Res. Int.* 37, 723-729

411 CAMPOS, J. A. D. B, ZUCOLOTO, M. L., BONAFÉ, F. S. S, JORDANI, P. C. and  
412 MAROCO, J. 2011. Reliability and validity of self-reported burnout in college students: A  
413 cross randomized comparison of paper-and-pencil vs. online administration. *Comp. Hum.*  
414 *Behavior.* 27, 1875-1883

415 CARTIER, R., RYTZ, A., LECOMTE, A., POBLETE, F., KRYSTLIK, J., BELIN, E. and  
416 MARTIN, N. 2006. Sorting procedure as an alternative to a product sensory map. *Food Qual.*  
417 *Pref. 17*, 562-571

418 CHAMBERS, E. IV., GODWIN, S. L. And VECCHIO, F. A. 2000. Cognitive strategies for  
419 reporting portion sizes using dietary recall procedures. *J. Am. Diet. Assoc. 100*, 891-897

420 DEHLHOLM, C., BROCKHOFF, P. B., MEINERT, L., AASLYNG, M. D. and BREDIE,  
421 W. L. P. 2012. Rapid descriptive sensory methods – Comparison of Free Multiple Sorting,  
422 Partial Napping, Napping, Flash Profiling and conventional profiling. *Food Qual. Pref. 26*,  
423 267-277

424 DÍAZ de RADA, V. and DOMÍNGUEZ-ÁLVAREZ, J. A. 2014. Response quality of self-  
425 administered questionnaires: A comparison between paper and web questionnaires. *Social*  
426 *Sci. Comp. Review. 32*, 256-269

427 GRAVLEE, C. C., BERNARD, H. R., MAXWELL, C. R. and JACOBSON, A. 2013.  
428 Mode effects in free-list elicitation: Comparing oral, written, and web-based data collection.  
429 *Social Sci. Comp. Review. 31*, 119-132

430 HILBERT, T. S. and RENKL, A. 2008. Concept mapping as a follow-up strategy to learning  
431 from texts: what characterizes good or poor mappers? *Instr. Sci. 36*, 53-73

432 HOPFER, H. and HEYMANN, H. 2013. A summary of projective mapping observations –  
433 The effect of replicates and shape, an individual performance measurements. *Food Qual.*  
434 *Pref. 28*, 164-181

435 HUSSON, F., JOSSE, J., LÊ, S. and MAZET, J. 2014. *Multivariate Exploratory Data*  
436 *Analysis and Data Mining with R (Version 1.28)*

437 JAEGER, S. R., CARDELLO, A. V. and SCHUTZ, H. G. 2013. Emotion questionnaires : A  
438 consumer-centric perspective. *Food Qual. Pref.* *30*, 229-241

439 JIMENEZ, M. J., CANET, W. and ALVAREZ, M. D. 2013. Sensory Description of Potato  
440 Puree Enriched with Individual Functional Ingredients and Their Blends. *J. Texture Stud.* *44*,  
441 301-316

442 KENNEDY, J. 2010. Evaluation of replicated projective mapping of granola bars. *J. Sens.*  
443 *Stud.* *25*, 672-684

444 KENNEDY, J. and HEYMANN, H. 2009. Projective mapping and descriptive analysis of  
445 milk and dark chocolates. *J. Sens. Stud.* *24*, 220-223

446 LAWLESS, H. T. and HEYMANN, H. 2010. *Sensory Evaluation of Food*. 2<sup>nd</sup> ed. Springer,  
447 New York, NY

448 LÊ, S., JOSSE, J. and HUSSON, F. 2008. FactoMineR: An R package for multivariate  
449 analysis. *J. Stat. Software.* *25*, 1-18

450

451 LE DIEN, S. and PAGÈS, J. 2003. Hierarchical multiple factor analysis: Application to the  
452 comparison of sensory profiles. *Food Qual. Pref.* *14*, 397-403

453 LOUW, L., MALHERBE, S., NAES, T., LAMBRECHTS, M. and VAN RENSBURG, P.  
454 2013. Validation of two Napping® techniques as rapid sensory screening tools for high  
455 alcohol products. *Food Qual. Pref.* *30*, 192-201

456 LOUW, L., OELOFSE, S., NAES, T., LAMBRECHTS, M., VAN RENSBURG, P. and  
457 NIEUWOUDT, H. 2014. Trained sensory panellists' response to product alcohol content in

458 the projective mapping task: observations on alcohol content, product complexity and prior  
459 knowledge. *Food Qual. Pref.* 34, 37-44

460 MIELBY, L. H., HOPFER, H., JENSEN, S., THYBO, A.K. and HEYMANN, H. 2014.  
461 Comparison of descriptive analysis, projective mapping and sorting performed on pictures of  
462 fruit and vegetable mixes. *Food Qual. Pref.* 35, 86-94

463 MOSKOWITZ, H. 2002. Mapping in product testing and sensory analysis: A well lit path or  
464 a dark statistical labyrinth? *J. Sens. Stud.* 17, 207-213

465 MOUSSAOUI, K. A. and VARELA, P. 2010. Exploring consumer product profiling  
466 techniques and their linkage to a quantitative descriptive analysis. *Food Qual. Pref.* 21, 1088-  
467 1089

468 NESTRUD, M. A. and LAWLESS, H. T. 2008. Perceptual mapping of citrus juices using  
469 projective mapping and profiling data from culinary professionals and consumers. *Food Qual.*  
470 *Pref.* 19, 431-438

471 NESTRUD, M. A. and LAWLESS, H. T. 2010. Perceptual mapping of apples and cheeses  
472 using projective mapping and sorting. *J. Sens. Stud.* 25, 390-405

473 PAGÈS, J. 2005. Collection and analysis of perceived product inter-distances using multiple  
474 factor analysis: Application to the study of 10 white wines from the Loire Valley. *Food Qual.*  
475 *Pref.* 16, 642-649

476 PAGÈS, J. and HUSSON, F. 2001. Inter-laboratory comparison of sensory profiles:  
477 Methodology and results. *Food Qual. Pref.* 12, 297-309

478 PERRIN, L., SYMONEAUX, R., MAÎTRE, I., ASSELIN, C., JOURJON, F. and PAGÈS, J.  
479 2008. Comparison of three sensory methods for use with the Napping® procedure: Case of  
480 ten wines from Loire valley. *Food Qual. Pref.* *19*, 1-11

481 R Core team. 2013. R: A language and environment for statistical computing. R Foundation  
482 for Statistical Computing, Vienna, Austria. <http://www.R-project.org/>. Last accessed  
483 02.01.2015.

484 RISVIK, E., McEWAN, J. A., COLWILL, J. S., ROGERS, R. and LYON, D. H. 1994.  
485 Projective mapping: A tool for sensory analysis and consumer research. *Food Qual. Pref.* *5*,  
486 263-269

487 RISVIK, E., McEWAN, J. A. and RØDBOTTEN, M. 1997. Evaluation of sensory profiling  
488 and projective mapping data. *Food Qual. I*, 63-71

489 ROBERT, P. and ESCOUFIER, Y. 1976. A unifying tool for linear multivariate statistical  
490 methods: the RV-coefficient. *Appl. Statist.* *25*, 257-265

491 RUSSELL, C. G., FLIGHT, I., LEPPARD, P., VAN LAWICK VAN PABST, J. A.,  
492 SYRETTE, J. A. and COX, D. N. 2004. A comparison of paper-and-pencil and computerised  
493 methods of "hard" laddering. *Food Qual. Pref.* *15*, 279-291

494 SANTOS, B. A., POLLONIO, M. A. R., CRUZ, A. G., MESSIAS, V. C., MONTEIRO, R.  
495 A., OLIVEIRA, T. L. C., FARIA, J. A. F., FREITAS, M. Q. and BOLINI, H. M. A. 2013.  
496 Ultra-flash profile and projective mapping for describing sensory attributes of prebiotic  
497 mortadellas. *Food Res. Int.* *54*, 1705-1711

498 SWANEY-STUEVE, M. and HEYMANN, H. 2002. A comparison between paper and  
499 computerized ballots and a study of simulated substitution between the two ballots used in  
500 descriptive analysis. *J. Sens. Stud.* *17*, 527-537

501 VALENTIN, D., CHOLLET, S., LELIÈVRE, M. and ABDI, H. 2012. Quick and dirty but  
502 still pretty good : a review of new descriptive methods in food science. *Int. J. Food Sci.*  
503 *Technol.* *47*, 1563-1578

504 VARELA, P. and ARES, G. 2012. Sensory profiling, the blurred line between sensory and  
505 consumer science. A review of novel methods for product characterization. *Food Res. Int.* *48*,  
506 893-908

507 VEINAND, B., GODEFROY, C., ADAM, C. and DELARUE, J. 2011. Highlight of  
508 important product characteristics for consumers. Comparison of three sensory descriptive  
509 methods performed by consumers. *Food Qual. Pref.* *22*, 474-485

510 VIDAL, L., SILVA CADENA, R., ANTÚNEZ, L., GIMENÉZ, A., VARELA, P. and ARES,  
511 G. 2014. Stability of sample configurations from projective mapping: How many consumers  
512 are necessary? *Food Qual. Pref.* *34*, 79-87

513 VICENTE, E., VARELA, P., DE SALDAMENDO, L. and ARES, G. 2014. Evaluation of the  
514 sensory characteristics of strawberry cultivars throughout the harvest season using projective  
515 mapping. *J. Sci. Food Agric.* *94*, 591-599

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517 Table 1: attributes significantly ( $p < 0.05$ ) correlated to dimensions 1 and 2 – 1<sup>st</sup> study

	<b>Paper based projective mapping</b>	<b>Computer based projective mapping</b>
<u>Dimension 1</u>	Bitter (-)	Bitter (-)
	Dark (+)	Dark (+)
	Fruity (+)	Fruity (+)
	Golden colour (+)	Golden colour (+)
	Malty (+)	Malty (+)
	Pale (-)	Pale (-)
	Sour (-)	Sour (-)
	Sweet (+)	Sweet (+)
	Caramel (+)	Clean taste (-)
	Cloudy (+)	Creamy (+)
	Corked (-)	Fizzy (-)
	Flowery (+)	Foamy (+)
	Hoppy (-)	Honey (+)
	Sweaty (-)	Lager (-)
	Thin (-)	Smooth (+)
	Urine flavour (-)	
	Watery (-)	
<u>Dimension 2</u>	Bland (-)	Bland (-)
	Mild smell (-)	Bitter after taste (-)
		Not sweet (-)
		Thin (-)
		Watery (-)

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520 Table 2: panellists' strategies for paper and computer PM tasks – 2<sup>nd</sup> study

<b>Dimension</b>	<b>Panellist</b>	<b>Paper</b>	<b>Computer</b>	<b>Similar</b>
<b>Holistic vs. attribute driven</b>	1	Holistic	Holistic	Yes
	2	Holistic	Holistic	Yes
	3	Attribute driven	Attribute driven	Yes
	4	Attribute driven	Attribute driven	Yes
	5	Holistic	Holistic	Yes
	6	Attribute driven	Attribute driven	Yes
	7	Holistic	Holistic at start - attribute driven towards end	Mostly
	8	Holistic	Holistic	Yes
	9	Attribute driven	Attribute driven	Yes
	10	Holistic	Holistic	Yes
<b>Grouping strategy</b>	1	Placed 1 <sup>st</sup> sample tasted on the map then others in relation to the 1 <sup>st</sup> one.	Looked for similar samples and grouped them together, placed the others in relation to these groups.	No
	2	Placed the 1 <sup>st</sup> sample in the top left hand side of the map, then the other samples in relation to it.	Placed the 1 <sup>st</sup> sample in the top left hand corner then the others in relation to it.	Yes
	3	Wrote attributes for each sample on top right hand side of map. Decided axis meaning. Placed each sample individually based on attributes intensities.	Typed attributes in sample tags during 1 <sup>st</sup> tasting. Decided axis meaning. Prepared map on bench and reproduced on screen. Clustered similar samples based on attributes intensities.	Mostly
	4	Decided axis meaning. Placed each sample individually based on attributes intensities.	Clustered samples by similarity based on specific attributes.	No
	5	Identified the oddest sample on 1 <sup>st</sup> tasting and placed it in one corner of the map; then placed the others (grouped for similarity) in relation to it.	Identified the oddest sample and placed it in one corner of the screen.	Yes
	6	Decided axis meaning: used main differences between 1 <sup>st</sup> and 2 <sup>nd</sup> sample to select axis meaning. Placed each sample individually based on attributes intensities.	Decided axis meaning. Placed each sample based on the intensities of attributes represented by the axis but grouped them for similarity using other attributes too.	Mostly
	7	Compared samples pairwise looking for similarities. Used appearance then aroma, followed by taste to compare the beers.	Compared samples pairwise looking for similarities. Used appearance, then aroma followed by taste to compare the beers.	Yes
	8	Rough map on 1 <sup>st</sup> tasting prepared on the bench, committed to paper on 2 <sup>nd</sup>	Rough map on 1 <sup>st</sup> tasting; fine-tuned on 2 <sup>nd</sup> tasting.	Yes

		tasting.		
	9	Separated the samples by colour then smelled them all writing down attributes along, then tasted all the samples writing down attributes before finishing the map. Used arrows to link descriptors to crosses on the map.	Prepared a rough map on the bench, decided on attributes to discriminate between samples before reproducing the map on the screen.	No
	10	Identified similar samples to group together.	Identified similar samples to group together.	Yes
<b>Axis meaning</b>	1	No articulated meaning for axis.	No articulated meaning for axis.	Yes
	2	No articulated meaning for axis.	No articulated meaning for axis.	Yes
	3	Appearance/colour selected as dimension before starting to taste. Complemented by bitter/sweet after 3 samples.	Appearance/colour selected as dimension before starting to taste. Complemented by bitter/sweet after a few samples.	Yes
	4	After tasting 2 samples, axis meaning selected as flat – frothy (x axis) and sweet – bitter (y axis).	No articulated axis meaning.	No
	5	No articulated meaning for axis.	No articulated meaning for axis.	Yes
	6	Bitterness and thickness established right away as axis meaning.	Bitterness and thickness established as axis meaning after a few samples.	Yes
	7	No articulated meaning for axis.	No articulated meaning for axis but placed last samples in relation to others citing colour and sweetness.	Mostly
	8	Perceived product category used ("traditional beers" at the top).	Perceived product category used ("real ales" or "low quality").	Yes
	9	X axis related to colour, y axis not specified.	Selected attributes for the x and y axis early on "I have now selected the attributes I'll use to build my map" but does not speak them out loud.	Mostly
	10	Not consciously articulated but used "sweetness" and "light" to characterise and separate groups of samples.	Not consciously articulated but used "bitter" and "light straw" to characterise and separate groups of samples.	Yes
<b>Early attention focus</b>	1	Map: built the map then focused on attributes.	Map: built the map then generated attributes.	Yes
	2	Map: built the map then wrote attributes down.	Attributes: typed attributes in sample tags then generated the map.	No
	3	Attributes: wrote attributes down for all samples in the top left corner of the map before generating the map.	Attributes: typed attributes for each sample in the sample tags before generating the map.	Yes

4	Concurrent: wrote the attributes down as the map was generated.	All samples dragged onto the screen to type attributes. Appearance attributes typed first then concurrent, attributes/map.	Mostly
5	Map: generated the map then wrote the attributes on re-tasting/finalising the map.	Map: typed the attributes when happy with the map.	Yes
6	Concurrent: described samples using the axis meaning and sample characteristics to generate the map.	Concurrent: typed the attributes in the sample tags as they were tasted and placed on the map.	Yes
7	Concurrent: wrote the attributes down as the map was generated.	Concurrent: typed the attributes in the sample tags as they were tasted and placed on the map.	Yes
8	Map: rough generated the map then wrote the attributes on re-tasting/finalising the map.	Concurrent: typed the attributes in the sample tags as they were tasted and roughly placed on the map. Map fine-tuned on re-tasting.	Mostly
9	Attributes: all samples assessed for appearance then aroma then taste.	Map: quick taste tour to build map on bench then re-taste to fine-tune and type sample descriptions.	No
10	Attributes: described all the samples before placing them on the map and writing down attributes.	Attributes: described all the samples before placing them on the map and typing in the attributes.	Yes

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