

Panelists' performances and strategies in paper based and computer based projective mapping

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Published version

SAVIDAN, Capucine and MORRIS, Cecile (2015). Panelists' performances and strategies in paper based and computer based projective mapping. *Journal of Sensory Studies*, 30 (2), 145-155.

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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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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 took 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 (1st 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 3rd 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

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516

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

	Paper based projective mapping	Computer based projective mapping
<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 – 2nd study

Dimension	Panellist	Paper	Computer	Similar
Holistic vs. attribute driven	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
Grouping strategy	1	Placed 1 st sample tasted on the map then others in relation to the 1 st one.	Looked for similar samples and grouped them together, placed the others in relation to these groups.	No
	2	Placed the 1 st sample in the top left hand side of the map, then the other samples in relation to it.	Placed the 1 st 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 st 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 st 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 st and 2 nd 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 st tasting prepared on the bench, committed to paper on 2 nd	Rough map on 1 st tasting; fine-tuned on 2 nd 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
Axis meaning	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
Early attention focus	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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