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Identifying drivers of liking and characterizing the ideal product thanks to Free-Comment

Benjamin Mahieu, Michel Visalli, Pascal Schlich

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1 Title

2 Identifying drivers of liking and characterizing the ideal product thanks to Free-
3 Comment

4 Authors

5 Benjamin Mahieu^{1,2}, Michel Visalli^{1,2}, Pascal Schlich^{1,2}

6 ¹Centre des Sciences du Goût et de l'Alimentation, AgroSup Dijon, CNRS, INRAE,
7 Université Bourgogne Franche-Comté, F-21000 Dijon, France.

8 ²INRAE, PROBE research infrastructure, ChemoSens facility, F-21000 Dijon, France

9 Corresponding author:

10 Benjamin Mahieu; Pascal Schlich

11 benjamin.mahieu@inrae.fr; pascal.schlich@inrae.fr

12 Centre des Sciences du Goût et de l'Alimentation, AgroSup Dijon, CNRS, INRAE,
13 Université Bourgogne Franche-Comté, F-21000 Dijon, France.

14 INRAE, PROBE research infrastructure, ChemoSens facility, F-21000 Dijon, France

15 Highlights

- 16 - Drivers of liking can be identified from Free-Comment (FC) data
- 17 - Ideal-Free-Comment (IFC) enables to characterize the ideal product with FC
- 18 - IFC enables to locate the ideal product on the FC product map
- 19 - Drivers of liking based on FC data and IFC are complementary tools

20 Abstract

21 Consumers' hedonic appreciation is important for the commercial success of a
22 product. To formulate appreciated products, sensory and hedonic data of some
23 existing products are often linked to each other. Because existing products represent
24 only a limited sensory space of investigation, asking consumers to characterize their
25 ideal product can provide relevant additional information to understand their

26 preferences. First, the paper investigates whether sensory drivers of liking can be
27 derived from linking Free-Comment (FC) and hedonic data. Second, Ideal-Free-
28 Comment (IFC) is introduced. IFC instructs consumers to describe actual products
29 and then their ideal product thanks to FC. IFC paired with liking scoring was used in a
30 [home-use](#) test with 483 consumers each evaluating from 1 to 14 (5.71 on average)
31 cooked hams from a list of 30 hams representative of the French market. Based on a
32 mixed linear model, relevant drivers of liking were identified from FC data. The
33 panel's average ideal product was consistent with the drivers of liking. Since
34 descriptors with opposite meanings characterized individual ideal products, a
35 consumer segmentation based on their ideal product was performed and resulted in
36 two segments. The two segments' ideal products mainly differed regarding their
37 flavor. Drivers of liking and the ideal product of the smaller segment ($\approx 15\%$ of the
38 consumers) were not well consistent suggesting this was a noise segment. Drivers of
39 liking based on FC data and IFC are complementary tools to understand consumers'
40 hedonic appreciation without the use of a pre-established list of descriptors.

41 **Keywords**

- 42 - Open-ended questions
- 43 - Drivers of liking
- 44 - Ideal-Free-Comment (IFC)
- 45 - Consumer segmentation
- 46 - Cooked ham
- 47 - Home-Use Test (HUT)

48 **1. Introduction**

49 Consumers' hedonic appreciation is one of the most important drivers of the
50 commercial success of a product. It is most often investigated using hedonic tests in
51 which a panel of consumers is instructed to score their overall liking of products.
52 Since liking is a function of the products' sensory characteristics ([Lagrange &](#)
53 [Norback, 1987](#)), investigating these characteristics is necessary to understand liking
54 and formulate appreciated products. For this reason, hedonic tests are often
55 performed conjointly to the sensory characterization of the products. Because
56 consumers were claimed not to be able to provide valid nor reliable sensory

57 characterization (Ares & Varela, 2017; Lawless & Heymann, 1999; Meilgaard, Civille,
58 & Carr, 1991; Stone & Sidel, 1993), this sensory characterization used to be
59 performed by sensory profiling using a trained panel.

60 Several methodologies have been developed to link sensory and hedonic data
61 among which preference mapping techniques (Carroll, 1972; Danzart, 2009;
62 Greenhoff & MacFie, 1994; McEwan, 1996; Schlich & McEwan, 1992) are likely the
63 most popular. Two major approaches can be distinguished among preference
64 mapping techniques: internal preference mapping and external preference mapping.
65 They mainly differ in the point of view they adopt (van Kleef, van Trijp, & Luning,
66 2006). Internal preference mapping puts the focus on the hedonic data: the product
67 space is obtained from liking scores and the sensory descriptor scores are regressed
68 into this space. On the contrary, external preference mapping puts the focus on the
69 sensory data: the product space is obtained from sensory descriptor scores and the
70 individual liking scores are regressed into this space. Worch (2013) proposed the so-
71 called prefMFA method that uses Multiple Factor Analysis (Escofier & Pagès, 1994)
72 to determine the shared dimensions between sensory and hedonic data.

73 During the last recent years, the affirmation upon which consumers are unable to
74 provide valid or reliable sensory characterization has been reconsidered. One of the
75 main reasons is that trained panels might consider descriptors and variations that are
76 irrelevant to consumers (Ares & Varela, 2017; ten Kleij & Musters, 2003). In addition,
77 several consumer methods were claimed to obtain more or less similar information as
78 the one provided by sensory profiling in practical applications (Ares & Varela, 2017;
79 Valentin, Chollet, Lelièvre, & Abdi, 2012; Varela & Ares, 2012). Among these
80 consumer methods, some were specifically designed to understand preferences and
81 to link hedonic data with consumer sensory data. Notably, Just-About-Right (JAR)
82 scales (see for example Popper (2014)) and Check-All-That-Apply (CATA) (Adams,
83 Williams, Lancaster, & Foley, 2007) paired with hedonic data collection and penalty-
84 lift analysis (Meyners, Castura, & Carr, 2013) belong to these methods. Other
85 methods sharing the same objective can be mentioned such as Preferred Attribute
86 Elicitation (Grygorczyk, Lesschaeve, Corredig, & Duizer, 2013), preference mapping
87 based on Sorting (Faye et al., 2006), and preference mapping based on CATA
88 (Dooley, Lee, & Meullenet, 2010).

89 Previous methodologies intend to understand the sensory characteristics that drive
90 the liking and the disliking of the products through the study of some existing
91 products, which necessarily restricts the sensory space investigated. This limitation
92 can affect the conclusions drawn since the ideal product does not necessarily lie
93 within the product space (van Trijp, Punter, Mickartz, & Kruithof, 2007). Indeed, since
94 only a limited number of products are presented to consumers then only a limited
95 number of combinations of sensory characteristics are represented and evaluated.
96 To circumvent this limitation, the Ideal-Profile-Method (IPM) (Moskowitz, 1972; van
97 Trijp et al., 2007; Worch, Lê, Punter, & Pagès, 2013) was proposed. In IPM,
98 consumers are instructed to rate the products on several descriptors from a pre-
99 established list using intensity scales. Right after the evaluation of every actual
100 product, consumers are instructed to do the same task but considering a virtual ideal
101 product. The idea is that the consumers provide for each descriptor the rating they
102 would have found ideal in the previous actual product. Recently, characterizing the
103 ideal product like the actual products has been successfully extended to other
104 methodologies than intensity scales such as CATA (Ares, Dauber, Fernández,
105 Giménez, & Varela, 2014; Ares et al., 2017; Ares, Varela, Rado, & Giménez, 2011;
106 Bruzzone et al., 2015), Projective Mapping (Ares et al., 2011) and Pairwise
107 Comparison (Brard & Lê, 2016). These studies suggest that characterizing the ideal
108 product is relevant even when it is not performed using intensity measurements of
109 each descriptor and when only a single ideal product is considered for each
110 consumer.

111 Until now, most of the existing methodologies that aim at investigating drivers of liking
112 and characterizing the ideal product are based on a pre-established list of
113 descriptors, which comes with several limitations. The list is tedious to establish and
114 represents a critical aspect for the relevance of the collected data as it may affect the
115 results of the study (Ares et al., 2013). The list may raise consumers' awareness on
116 descriptors they would not think about otherwise (Coulon-Leroy, Symoneaux,
117 Lawrence, Mehinagic, & Maitre, 2017; Kim, Hopkinson, van Hout, & Lee, 2017;
118 Krosnick, 1999). Since the list contains only a limited number of descriptors, it could
119 result in a loss of information and the collected data can be biased by the dumping
120 effect (Krosnick, 1999; Varela et al., 2018). When used in a CATA task, the list likely
121 leads to an acquiescence bias (Callegaro, Murakami, Tepman, & Henderson, 2015;

122 Kim et al., 2017; Krosnick, 1999), which encourages consumers to check the
123 proposed descriptors.

124 Luc, Lê, and Philippe (2020) took a step forward in the characterization of the ideal
125 product without the use of a pre-established list of descriptors by proposing the so-
126 called Free JAR profiling. In Free JAR profiling, consumers are instructed to describe
127 a set of products using free descriptions constrained to a JAR syntax. In Free JAR
128 profiling, the ideal product is not directly characterized since its characteristics are
129 derived from the Free JAR descriptions of the actual products. This can result in
130 some loss and/or some misleading information regarding the ideal product if the
131 actual products are not carefully chosen.

132 Free-Comment (FC) (ten Kleij & Musters, 2003), where consumers are instructed to
133 describe the products using their own terms into free descriptions without syntax
134 constraint, appears as a natural alternative to identify drivers of liking and to
135 characterize the ideal product avoiding the limitations from the existing
136 methodologies. Accordingly, first, the present paper investigates the relevance of FC
137 sensory data to be linked to hedonic data with the final aim of identifying drivers of
138 liking. Second, the Ideal-Free-Comment (IFC) method is introduced and its ability to
139 provide a relevant characterization of the ideal product is investigated. In IFC,
140 consumers are instructed to describe actual products and then their ideal product
141 thanks to FC. In comparison to Free JAR profiling, IFC renders the characterization
142 of the ideal product as independent as possible from the characterization of the
143 actual products with the same benefit of not restricting the sensory characterizations
144 to a pre-established list of descriptors. The final objective was to investigate whether
145 drivers of liking and the ideal product provide consistent, and eventually
146 complementary, information.

147 2. Material and methods

148 2.1. Participants

149 483 consumers from 7 French cities (Agen, Angers, Bourg en Bresse, Caen, Dijon,
150 La Rochelle, Strasbourg) were recruited by technical centers from the ACTIA network
151 and by the SensoStat Company. Among these consumers, 58% were females, 19%
152 were between 18 and 30 years old, 47% were between 31 and 51 years old and 34%

153 were more than 51 years old. They were selected as being consumers of cooked
154 ham at least once every two weeks and were informed that they should purchase and
155 evaluate a minimum of 4 different hams among a provided list of 30 hams widely
156 available on the French market. Compensation for their participation was 2.5 € for
157 each different evaluated product and no additional compensation was given to those
158 who evaluated more than 12 different products.

159 2.2. Products

160 A list of 30 cooked hams of the French Market was selected to span the variability of
161 fat and salt contents observed in this market. This sample was restricted to hams
162 without rind and excluded smoked, braised, spit-roasted, and flavored hams.

163 2.3. Data acquisition

164 2.3.1. General procedure

165 The consumers purchased the products they evaluated and performed the
166 evaluations at home. Each product they evaluated had to be one of the 30 products
167 belonging to the proposed list. An email was sent to the consumers to invite them to
168 connect to TimeSens© (INRAE, Dijon, France) each time they evaluated a product.
169 At each connection, the consumers had to type the European Article Numbering
170 (EAN) of the ham they purchased. The consumers could not start the evaluation of a
171 product they already evaluated as this was verified thanks to the EAN. To ensure
172 they bought the product, they had to take a picture of the package, before and after
173 opening. The study lasted 13 weeks and consumers could purchase hams whenever
174 they decided but they were restricted to a maximum of one evaluation per day.
175 Despite consumers were instructed to evaluate a minimum of 4 different hams and
176 were compensated up to 12 ones, some of them evaluated less than 4 and others
177 more than 12. Consequently, the number of hams evaluated by each consumer
178 actually ranged between 1 and 14 (mean = 5.71, sd = 2.47) resulting in a total of
179 2758 evaluations. The data from consumers not respecting instructions were kept, as
180 every information is good to take. The number of evaluations by ham ranged
181 between 8 and 263 (mean = 91.93, sd = 63.38).

182 2.3.2. Sensory and hedonic characterization of the actual products

183 For each evaluated product, it was recalled to consumers to evaluate and consume
184 the product on its own without extra food. They first performed an FC task by sensory
185 modality in the following order: visual aspect, texture in mouth, and flavor. For each
186 sensory modality, the following instructions were given to the consumers:

- 187 - Visual aspect: "Please describe the visual aspect of this ham"
- 188 - Texture in mouth: "Please describe the texture in mouth of this ham"
- 189 - Flavor: "Please describe the taste of this ham"

190 Right after the FC task, the consumers rated their liking of the product using a 0-10
191 VAS scale. Finally, the consumers had to provide their perception of the salt level,
192 the fat level, the tenderness, and the color intensity of the product using 5-points
193 Just-About-Right (JAR) scales.

194 After the sensory evaluation of the product, the consumers answered a few questions
195 concerning their motivations for having purchased this product.

196 2.3.3. Sensory characterization of the ideal product

197 When the consumers decided to stop purchasing and evaluating products, they
198 connected to TimeSens© and selected the corresponding option. This led them to
199 answer a final questionnaire. In this questionnaire, they had to describe their ideal
200 product using FC descriptions according to the same three sensory modalities used
201 to describe the actual products. For each sensory modality, the following instructions
202 were given to the consumers:

- 203 - Visual aspect: "Please describe the visual aspect of an ideal ham in your
204 opinion"
- 205 - Texture in mouth: "Please describe the texture in mouth of an ideal ham in
206 your opinion"
- 207 - Flavor: "Please describe the taste of an ideal ham in your opinion".

208 Some consumers did not answer the final questionnaire, resulting in a final number of
209 415 evaluations for the ideal product.

210 2.4. Data analyses

211 All FC data treatments and analyses were performed using R 4.0.2 (R Core Team,
212 2020). The lexicon provided with IRaMuTeQ© (Ratinaud, 2014) software was used
213 for lemmatization and part-of-speech tagging.

214 Since the focus is on IFC, JAR scales and motivations for purchasing the products
215 were not analyzed in this paper.

216 2.4.1. FC data treatment

217 2.4.1.1. FC descriptions of the actual products

218 As FC descriptions were collected in French, all subsequent treatments were
219 performed in French. The descriptors resulting from the treatments were then
220 translated into English for the present paper. The English-French correspondence of
221 the descriptors can be found in the appendix.

222 The FC datasets from each of the three sensory modalities (visual aspect, texture in
223 mouth, and flavor) were treated separately with the method described in (Mahieu,
224 Visalli, Thomas, & Schlich, 2020) and summarized thereafter. The FC descriptions of
225 the ideal product were not involved in this process.

226 The descriptions were first cleaned, lemmatized, and filtered. Then, the descriptors
227 with similar meanings were grouped into latent-descriptors relying on an ascendant
228 hierarchical classification.

229 Among all the descriptors and latent-descriptors, only those mentioned throughout at
230 least 5% of the evaluations of at least one product were retained for further analysis.

231 Finally, the descriptors were cross-tabulated with the consumers and the products
232 indicating whether each descriptor was cited in the corresponding evaluation or not.

233 2.4.1.2. FC descriptions of the ideal product

234 The FC descriptions of the ideal product were treated the same manner as the FC
235 descriptions of the actual products. They were cleaned, lemmatized, and filtered
236 using the same filters that those used for the actual products, and the same
237 descriptor groupings were applied. Some additional descriptors not mentioned for the
238 actual products appeared in the descriptions of the ideal product. However, these
239 additional descriptors were not mentioned by at least 5% of the consumers that
240 described their ideal product and they were thus not retained for further analyses.

241 Finally, the descriptors were cross-tabulated with the consumers indicating whether
242 each descriptor was cited by the corresponding consumer in its description of the
243 ideal product or not.

244 *2.4.2. Panel level*

245 *2.4.2.1. Drivers of liking*

246 The liking scores were regressed against the consumer factor, the product factor,
247 and the descriptor factors using a mixed linear model fitted on all evaluations. Each
248 descriptor factor had two levels: absence or presence, the absence level being the
249 reference one. The descriptor factors and the product factor were considered as fixed
250 while the consumer factor was considered as random. The regression loading of
251 each descriptor was considered as an estimate of its impact on liking scores.
252 Confidence intervals ($\alpha = 5\%$) for the regression loadings were computed using the
253 Satterthwaite approximation (Giesbrecht & Burns, 1985; Hrong-Tai Fai & Cornelius,
254 1996; Satterthwaite, 1946).

255 *2.4.2.2. Ideal product*

256 The proportion of citations of each mentioned descriptor in the FC descriptions of the
257 ideal product were computed. Confidence intervals ($\alpha = 5\%$) for these proportions
258 were computed based on bootstrap resamplings of the consumers (1000
259 simulations). Descriptors significantly more frequently cited for the ideal product
260 relatively to the actual products were investigated using multiple-response
261 hypergeometric tests (Mahieu, Schlich, Visalli, & Cardot, 2021) with a one-sided
262 greater alternative hypothesis ($\alpha = 5\%$). For these tests, the random hypergeometric
263 samplings to estimate the null distribution were performed using the FC descriptions
264 of the actual products provided by the consumers having described their ideal
265 product.

266 For each of the three sensory modalities, a multiple-response Correspondence
267 Analysis (MR-CA) (Mahieu et al., 2021) was performed based on the descriptor
268 citation proportions for the actual products. The ideal product was projected as a
269 supplementary observation (based on its own descriptor citation proportions) into the
270 sensory space depicted by the actual products. Confidence ellipse ($\alpha = 5\%$) for the
271 ideal product coordinates was build based on bootstrap resampling of the consumers

272 (1000 simulations). Finally, the vector of mean liking scores of the actual products
273 was projected as a supplementary variable into the sensory space by computing its
274 weighted correlation coefficient with the MR-CA axes and using the same weight as
275 the MR-CA. This was performed to link the mean liking scores to the position of the
276 ideal product.

277 2.4.3. Consumer segments

278 2.4.3.1. Segmentation of the consumers based on their ideal product

279 The consumers were segmented based on their FC descriptions of the ideal product
280 considering the three sensory modalities and using a mixture-model-based clustering
281 for nominal data (Linzer & Lewis, 2011). The model assumes the data coming from a
282 finite mixture of K class-conditional probability distributions. The mixing proportions
283 and the class-conditional probability distributions are estimated by maximizing the
284 log-likelihood of the model using the expectation-maximization (EM) algorithm
285 (Dempster, Laird, & Rubin, 1977). The models ranging from K = 1 class to K = 10
286 classes were built. The “best” model was selected as the one having the lowest mean
287 of its AIC (Akaike, 1974) and BIC (Schwarz, 1978). This resulted in retaining the two-
288 class model. Finally, each consumer was affected to a class using a *maximum a*
289 *posteriori* (MAP) decision rule. This resulted in two segments respectively composed
290 of 351 (G1) and 64 (G2) consumers.

291 2.4.3.2. Characterization of each segment of consumers

292 Potential differences between the two segments in terms of gender repartition and
293 age group repartition were investigated using a chi-square test ($\alpha = 5\%$). Potential
294 differences between the two segments in terms of average frequency of consumption
295 of cooked hams by month were investigated using a bilateral t-test ($\alpha = 5\%$).

296 2.4.3.3. Ideal product of each segment of consumers

297 The same computations as presented in section 2.5.1.2 were performed within each
298 segment.

299 2.4.3.4. Drivers of liking of each segment of consumers

300 The same computations as presented in section 2.5.1.1 were performed within each
301 segment. The drivers of liking of each segment were investigated to be compared to
302 the ideal product of the corresponding segment.

303 3. Results

304 3.1. Panel level

305 3.1.1. Drivers of liking

306 Fig. 1 shows that the identified drivers of liking make sense from a sensory point of
307 view. The negatively connoted descriptors (e.g. *F_insipid*, *T_elastic_rubbery*, etc.)
308 were diagnosed as negative drivers of liking. On the contrary, the positively connoted
309 descriptors (e.g. *F_fragrant*, *T_soft_tender_melting*, etc.) were diagnosed as positive
310 drivers of liking. Some less trivial information is also shown in Fig. 1. For example,
311 observing *F_not_salty* as a driver of liking and *F_salty* as a driver of disliking can be
312 useful information, especially in a nutritional context. It appears in Fig. 1 that flavor
313 impacted more liking than the texture in mouth which itself impacted more liking than
314 the visual aspect. Finally, it can be seen in Fig. 1 that there were more drivers of
315 disliking than drivers of liking. Also, drivers of disliking had more impact on liking
316 scores in absolute value than drivers of liking.

317 3.1.2. Ideal product

318 Fig. 2 shows that the mentioned descriptors in the FC descriptions of the ideal
319 product were relevant as no negatively connoted descriptors were mentioned, which
320 confirms that the consumers understood the concept of describing their ideal product.
321 Some characteristics appeared very important to be found in the ideal product:
322 *V_not_fat*, *V_pink*, *V_soft_tender*, *F_not_salty*. The descriptors significantly more
323 frequently cited for the ideal product relatively to the actual products were consistent
324 with the identified drivers of liking. However, some differences can still be noticed.
325 One descriptor significantly associated with the ideal product was not identified as a
326 driver of liking: a “natural” visual appearance (*V_natural*). On the contrary, *F_fragrant*
327 identified as a driver of liking was not cited in the FC descriptions of the ideal product.
328 Finally, some opposite descriptors (e.g. *F_salty* vs. *F_not_salty*) were mentioned in

329 FC descriptions of the ideal product which justifies investigating if consumer
330 segments exist (see Section 3.2).

331 For the three sensory modalities, Fig. 3 (note that *IdealG1*, *IdealG2*, *LikingG1* and
332 *LikingG2* refer to a subsequent segmentation discussed later in section 3.2) shows
333 that the ideal product achieved the most extreme coordinates in the direction of the
334 liking among all the products and lied in a region of the sensory space that none of
335 the actual products reached. The first point confirms that the consumers understood
336 the concept of describing their ideal product and suggests that they provided ideal
337 product descriptions consistent with their liking scores. The second point suggests
338 that none of the actual products was ideal and that gathering descriptions of the ideal
339 product can provide relevant information. It is worth noticing that even if the ideal
340 product lied in a particular region of the sensory space, it was not the most distant
341 product from the average. This statement is true for the three sensory modalities and
342 suggests that the ideal product might be realistic. Interestingly, the confidence ellipse
343 of the ideal product was larger for the flavor modality than for the two other sensory
344 modalities. This is likely because consumers were more consensual in describing
345 their ideal product regarding visual aspect and texture in mouth than regarding flavor
346 and reinforces that investigating if consumer segments exist might be relevant.

347 Fig. 3 also suggests that the flavor modality is the most important regarding hedonic
348 appreciation. This is further confirmed by the average absolute weighted correlation
349 of the mean liking scores with the whole sensory axes: 0.139 for visual aspect, 0.201
350 for texture in mouth, and 0.261 for flavor. Finally, it is interesting to notice that this
351 ranking of the sensory modalities regarding the link between their sensory axes and
352 the mean liking scores is the same as the ranking observed for the drivers of liking
353 regarding the impact of each sensory modality on the liking scores.

354 3.2. Consumer segments

355 3.2.1. Characterization of each segment of consumers

356 The two segment were not statistically different regarding their gender repartition
357 ($\text{Chi}^2 = 0.074$, $\text{df} = 1$, $p = 0.7857$), their age group repartition ($\text{Chi}^2 = 2.771$, $\text{df} = 2$, $p =$
358 0.2502), and their average frequency of consumption of cooked hams by month ($t = -$
359 0.5802 , $\text{df} = 374$, $p = 0.5621$).

360 3.2.2. Ideal product of each segment of consumers

361 Fig. 4 shows that the two segments of consumers are interpretable. The ideal
362 products of the two segments mainly differed regarding their flavor. The ideal product
363 of G1 was described as *F_not_salty* approximately half of the time while it was never
364 described as *F_salty*. On the contrary, the ideal product of G2 was always described
365 as *F_salty* while it was never described as *F_not_salty*. This suggests that two types
366 of consumers exist. Those that would like their ideal product not to be salty and those
367 that would like their ideal product to be salty, the “salty lovers” being fewer ($\approx 15\%$ of
368 the consumers) than the others. Other smaller differences can be noticed between
369 the ideal products of the two segments: the ideal product of G1 was more often
370 described as *F_ham_taste* and *F_spicy_stocks_aromatics* than the one of G2.

371 Fig. 3 confirms the results from Fig. 4: the ideal products of the two segments differed
372 regarding their flavor but neither their texture in mouth nor their visual aspect. Not
373 surprisingly, regarding the flavor modality, the two ideal products were opposed on
374 the second dimension, which was a gradient of saltiness. Fig. 3 shows that the ideal
375 product of G1 is very close and thus similar to that of the panel. This makes sense
376 since G1 represents an overwhelming majority as compared to G2. Regarding, the
377 mean liking scores, the two segments appeared to have a similar pattern, close to
378 that of the panel. G1 seemed more consistent than G2 because its ideal product is
379 located farther away in the direction of its mean liking scores for the flavor modality.

380 3.2.3. Drivers of liking of each segment of consumers

381 Fig. 5 shows that the drivers of liking of each segment were only partially consistent
382 with their corresponding ideal product. Regarding saltiness, which was the main
383 difference between the two ideal products, the drivers of liking of G1 were perfectly
384 consistent with its ideal product: *F_not_salty* was a driver of liking and *F_salty* was a
385 driver of disliking. For G2, the loading of *F_salty* was positive as opposed to this
386 same loading for G1, but not significant. The loading of *F_not_salty* was also not
387 significant but it was positive and higher than that of *F_salty*. This reinforces the
388 evoked doubt (Fig. 3) on the consistency of G2. Regarding *F_ham_taste* and
389 *F_spicy_stocks_aromatics*, which were the other main differences between the two
390 ideal products, *F_ham_taste* was a driver of liking for the two segments and with the
391 same intensity and *F_spicy_stocks_aromatics* was a driver of liking for G1 and not

392 G2. However, this difference between G1 and G2 might be due to the different
393 number of consumers in the two segments which led to the confidence intervals of
394 G2 being larger than for G1. The fact that the loading of *F_spicy_stocks_aromatics*
395 was higher for G2 than for G1 reinforces this line of reasoning. Overall, the main
396 differences between the two ideal products were only moderately recovered by
397 comparing the drivers of liking of each segment. However, regarding the most
398 important difference, which was the level of saltiness, G1 had drivers of liking
399 consistent with its ideal product and a trend of consistency existed for G2 since its
400 loading for *F_salty* was positive as opposed to G1.

401 4. Discussion

402 4.1. Drivers of liking vs. ideal product

403 The ideal product and the drivers of liking are different approaches that have their
404 benefits and drawbacks. The drivers of liking are implicit and thus not subject to
405 cognitive and attitudinal bias unlike ideal product descriptions (Li, Hayes, & Ziegler,
406 2015). However, drivers of liking depend on the actual product space. This constraint
407 could result in some loss and/or some misleading information if too many sensory
408 characteristics are confused and/or not well represented by the actual product space.
409 Since the ideal product does not depend directly on the actual product space, it
410 enables exploring a larger sensory space than that depicted by the actual products
411 (Worch, Crine, Gruel, & Lê, 2014).

412 Overall, the ideal product and the drivers of liking should be considered
413 complementary rather than competitors: they reinforce and validate each other.
414 Drivers of liking which are significantly and frequently associated with the ideal
415 product are definitely important characteristics regarding appreciation. In the specific
416 context of FC, they are even more complimentary since some obvious and logical
417 characteristics (e.g. *F_fragrant* in this study) may not be mentioned in the
418 descriptions of the ideal product, as they are essential and natural. On the contrary,
419 some characteristics confused and/or rarely present in the actual products (e.g.
420 *V_natural* in this study) can be caught only thanks to the ideal product
421 characterization.

422 In this study, drivers of liking and the panel's average ideal product provided
423 information in agreement with each other. This suggests that this information can be
424 used from a product development point of view. Especially, including less salt in the
425 manufacturing process of the cooked hams would be beneficial from a nutritional
426 point of view and could possibly increase hedonic appreciation, but certainly not
427 decrease it.

428 4.2. Panel level vs. consumer segments for the ideal product

429 To the best of our knowledge, only one study previously proposed to segment the
430 consumers based on their ideal product (Chan, Kwong, & Hu, 2012). Segmenting the
431 consumers based on their ideal product makes sense only in two situations. The first
432 one is when opposite descriptors (e.g. *salty* vs. *not_salty*) are used in individual ideal
433 product descriptions. The second case is when the description of the ideal product is
434 highly variable among consumers. To determine if segmenting the consumers is
435 relevant, and when it is, the number of segments to consider should be determined
436 using objective criteria. Depending on the strategy of clustering adopted, different
437 criteria exist. When mixture models are used, as in this study, information criteria
438 such as AIC (Akaike, 1974) and BIC (Schwarz, 1978) can be used. When
439 hierarchical clustering and/or *k*-means algorithm are used, quality of clustering
440 indexes such as the Silhouette index (Rousseeuw, 1987) and the Gap statistic
441 (Tibshirani, Walther, & Hastie, 2001) can be used.

442 Even when segmenting the consumers based on their ideal product appears relevant
443 from both a qualitative and a statistical point of view, checking the consistency of
444 each segment is important (Brard & Lê, 2016; Worch et al., 2014; Worch, Lê, Punter,
445 & Pagès, 2012a, 2012b). If the ideal product of one or more segments does not
446 make sense regarding their drivers of liking, segmenting the consumers is
447 questionable. Similarly, when the segments share common drivers of liking but have
448 a different ideal product, segmenting is questionable. In this context, to better
449 understand the differences between the ideal products of each segment, using
450 mapping techniques (e.g. factorial analyses) and absolute measurements (e.g.
451 probabilities of citations) are useful and should be used conjointly. Further,
452 considering that some consumers could eventually provide ideal product descriptions
453 based on non-sensory criteria (e.g. health) (Worch et al., 2013) could help

454 understanding some non-consistent segments. Indeed some consumers could like
455 sweet products but their ideal product could be described as not sweet because they
456 are diabetics for example. However, since the ideal descriptions are instructed to be
457 provided based on the sensory perception (visual aspect, texture in mouth and flavor
458 in this study) this is unlikely to occur.

459 If different segments of consumers are identified, but one or some of them are of a
460 too-small size, then one should not consider the segmentation (Worch et al., 2012a,
461 2012b).

462 In the present paper, G1 highly dominated G2 in terms of size. Further, the
463 consistency of G2 was highly questionable, and G1 and G2 had no clear difference in
464 their drivers of liking except maybe on the level of saltiness. This suggests that for
465 this paper, the analyses performed at the panel level considering a single ideal
466 product are likely the most relevant. Alternatively, as suggested by (Worch et al.,
467 2012a, 2012b), the ideal product descriptions coming from the consumers of G2
468 could be dropped from the analysis by considering only those from G1.

469 4.3. Limitations

470 A first limitation comes from the uncommon data collection procedure of this study.
471 Indeed, to the best of our knowledge, it is the first time that sensory and hedonic data
472 are gathered from consumers purchasing the products they evaluate, which resulted
473 in unbalanced data for the actual products. This uncommon procedure does not
474 appear to be a major limitation as the data make sense. However, it worth
475 emphasizing that the liking scores of the actual products may have been
476 overestimated. Indeed, because consumers selected the products they evaluated,
477 some of them may have selected products they usually purchase and like. Knowing
478 that 20% of the evaluations among the 2758 ones were performed on usually
479 purchased hams and that an average overall liking score of 6.35 (all products
480 combined) was observed, the previous assertion could be at least partly verified.
481 However, other strategies of selection from the consumers may have occurred such
482 as selecting less expensive ones to maximize income from compensations, testing
483 more expensive ones as they were partly refunded by the compensations, or
484 selecting hams based on their labels and/or allegations. These other strategies,
485 considered together with the requirement that, for being compensated, the

486 consumers had to evaluate at least 4 different hams from the list, are the most likely
487 explanations to the fact that most of the hams belonging to the list were evaluated a
488 fair number of times, thus limiting the liking overestimation. Another point worth
489 emphasizing is that, since the consumers selected their evaluated products, they
490 may have restricted the product space and with that, the range of encountered
491 sensory characteristics, which may have affected the ideal product descriptions
492 provided after the evaluations of actual products. Indeed, consumers likely defined
493 what they like and dislike based on the evaluations of actual products. Depending on
494 the practitioners' aims, if gathering less "informed" ideal product descriptions is of
495 interest, consumers could be instructed to provide them before evaluations of actual
496 products but this could inversely affect actual products descriptions. Anyway,
497 investigating the method presented in this paper with a more "conventional"
498 experimental procedure might be an interesting direction for some future research. In
499 particular, comparing the consumer segments resulting from a segmentation on
500 either ideal product data or liking data would be of great interest. Segmenting
501 consumers based on liking data was not performed in this study because of the
502 uncommon experimental design that resulted in a "product by consumer" matrix of
503 liking scores having 81% of missing data.

504 A second limitation comes from the IFC method and the data analysis procedure
505 proposed in this study. More specifically, if some descriptors not present in the FC
506 descriptions of the actual products are mentioned in the FC descriptions of the ideal
507 product, the projection of the ideal product into the sensory space depicted by the
508 actual products can only be performed on basis of the descriptors shared by the
509 actual and the ideal product descriptions. However, this is not a major limitation since
510 the aim of this projection is to investigate the position of the ideal product relative to
511 the actual products, which make sense to be performed on the same set of
512 descriptors. All the other analyses presented in this study can be performed
513 equivalently with additional descriptors for the ideal product as compared to the
514 actual products. Finally, it has to be mentioned that if this situation occurs, it is a nice
515 argument in favor of IFC since no other existing method can investigate the hedonic
516 importance of descriptors not present within the actual product space.

517 5. Conclusion

518 The paper proposes to use Free-Comment (FC) sensory data to be used in the well-
519 established link between sensory and hedonic data. Further, it introduced a new
520 methodology called Ideal-Free-Comment (IFC) where consumers are instructed to
521 describe actual products and then their ideal product thanks to FC. This enables
522 investigating drivers of liking and characterizing the ideal product without the use of a
523 pre-established list of descriptors, which *de facto* avoids inherent limitations to any
524 pre-established list. Further, since the characterization of the ideal product is directly
525 performed, it does not depend on the actual product space, and the hedonic
526 importance of descriptors confused and/or rarely present in the actual products can
527 thus be investigated. Identification of drivers of liking based on FC data and IFC were
528 used on cooked hams with consumers purchasing the products they evaluated at
529 home and it showed relevant results. Drivers of liking based on FC data and IFC
530 provide sensory analysts with new complementary tools to understand consumers'
531 hedonic appreciation without the use of a pre-established list of descriptors.

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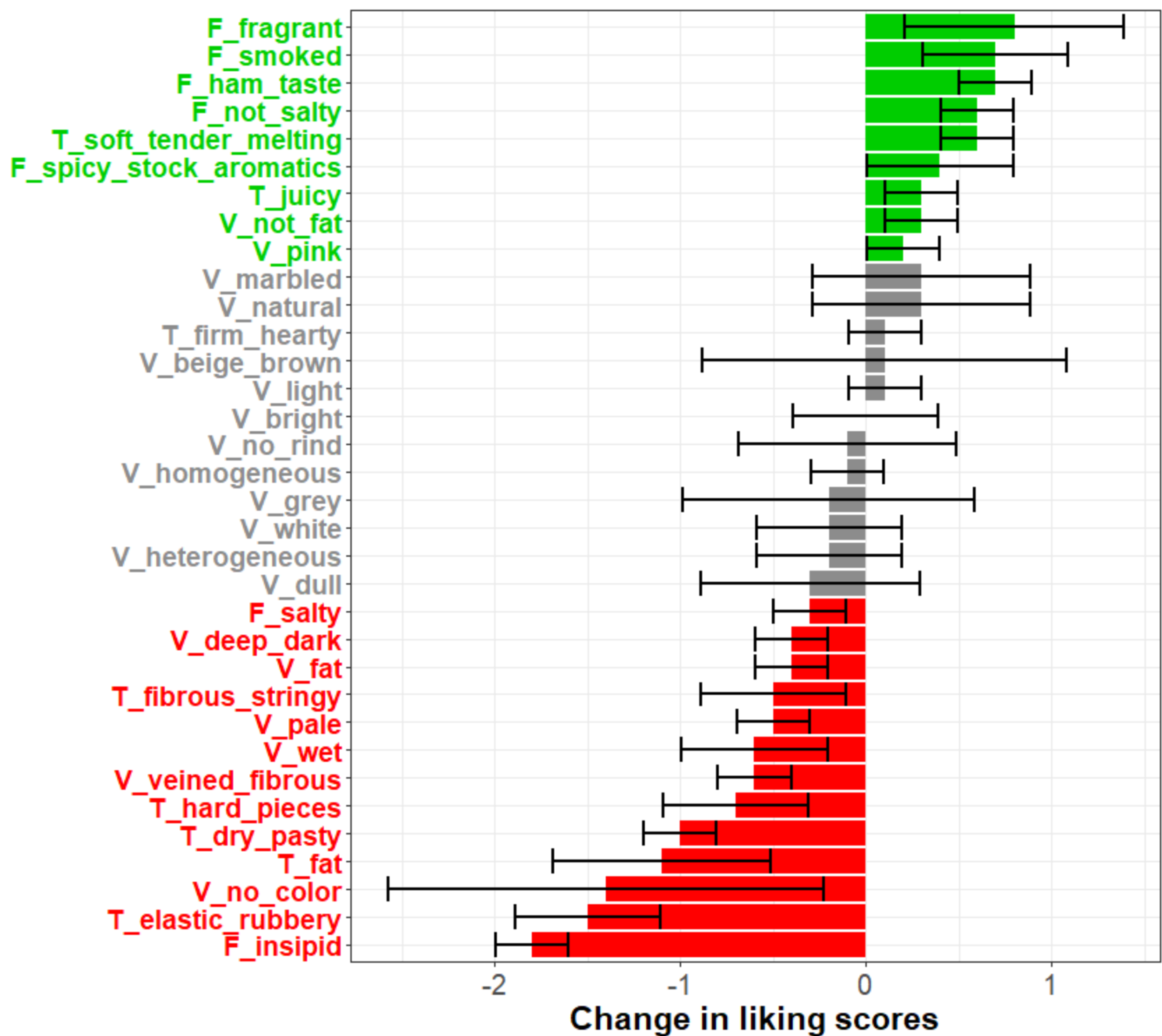
Fig. 1: Regression loadings of each descriptor with their respective confidence intervals ($\alpha = 5\%$). V stands for the visual descriptors, T stands for the texture in mouth descriptors and F stands for the flavor descriptors. Green (resp. red) bars represent significant ($\alpha = 5\%$) positive (resp. negative) drivers of liking.

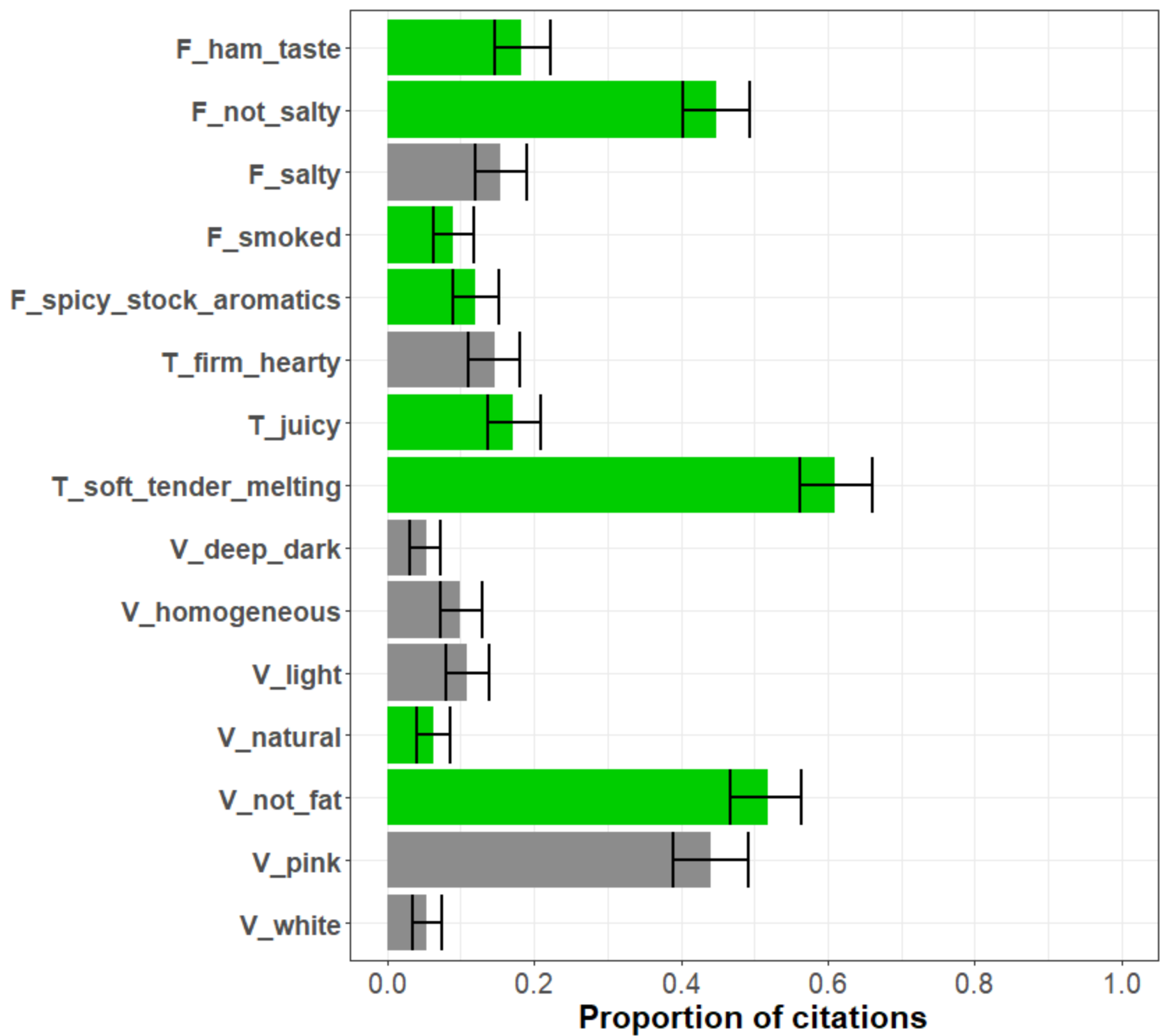
Fig. 2: Proportions of citation of descriptors mentioned in the FC descriptions of the ideal product with their respective confidence intervals ($\alpha = 5\%$). Green bars represent descriptors significantly more frequently cited for the ideal product relatively to the actual products (multiple-response hypergeometric test, $\alpha = 5\%$).

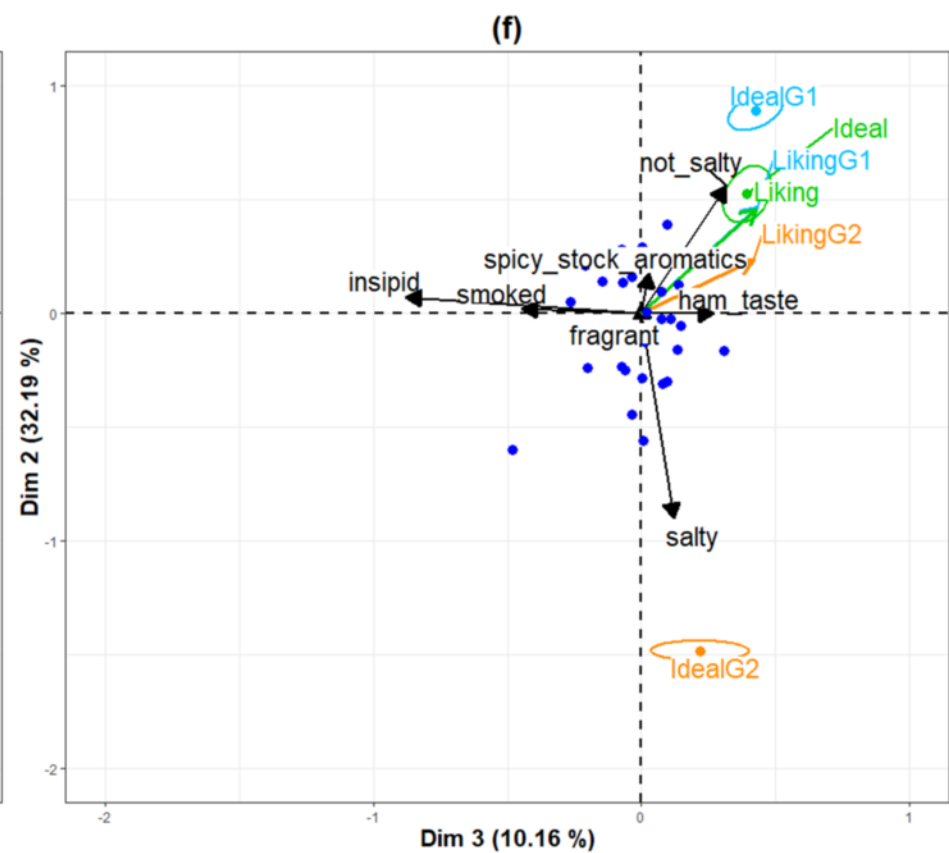
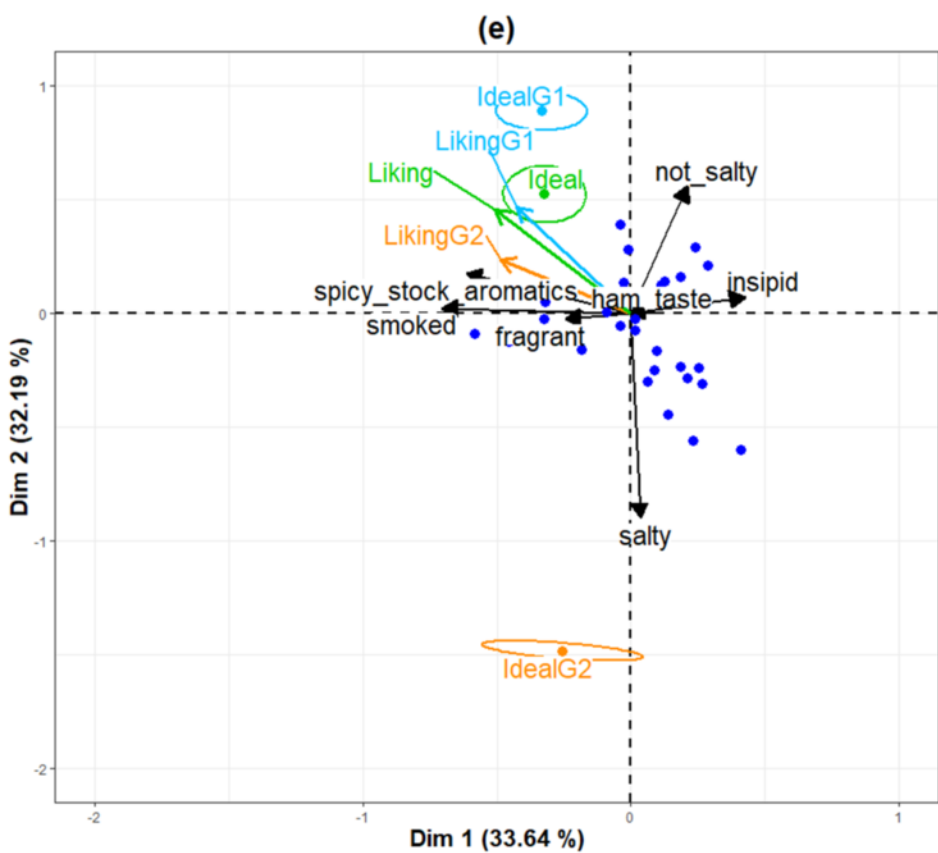
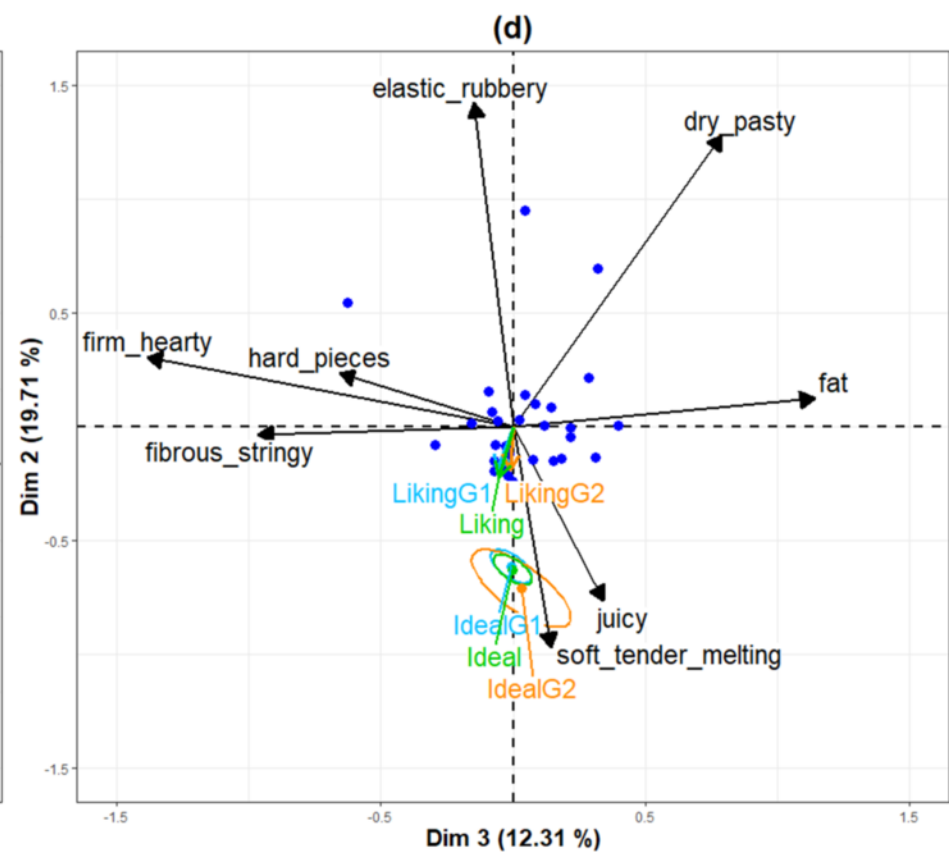
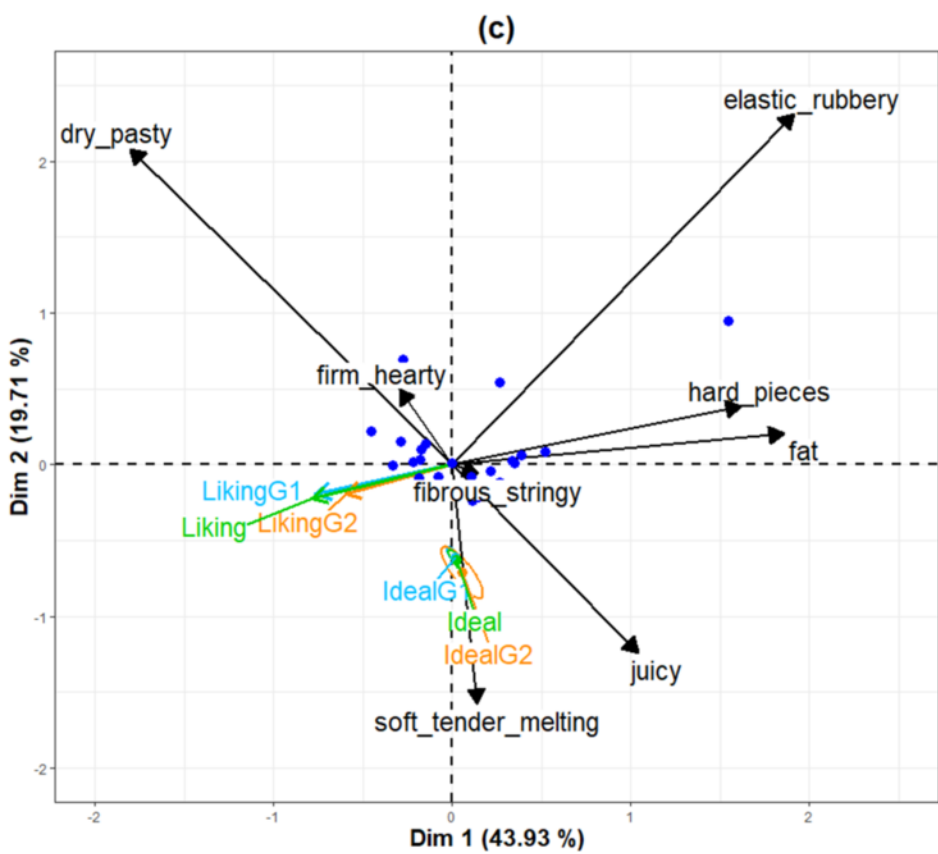
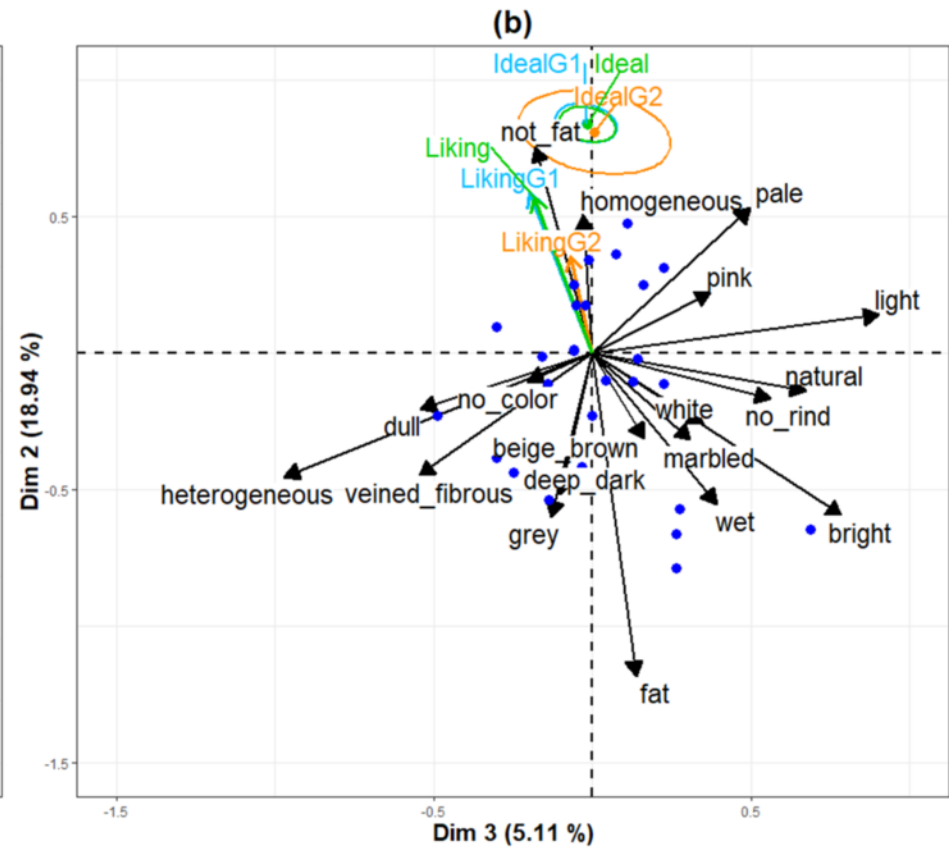
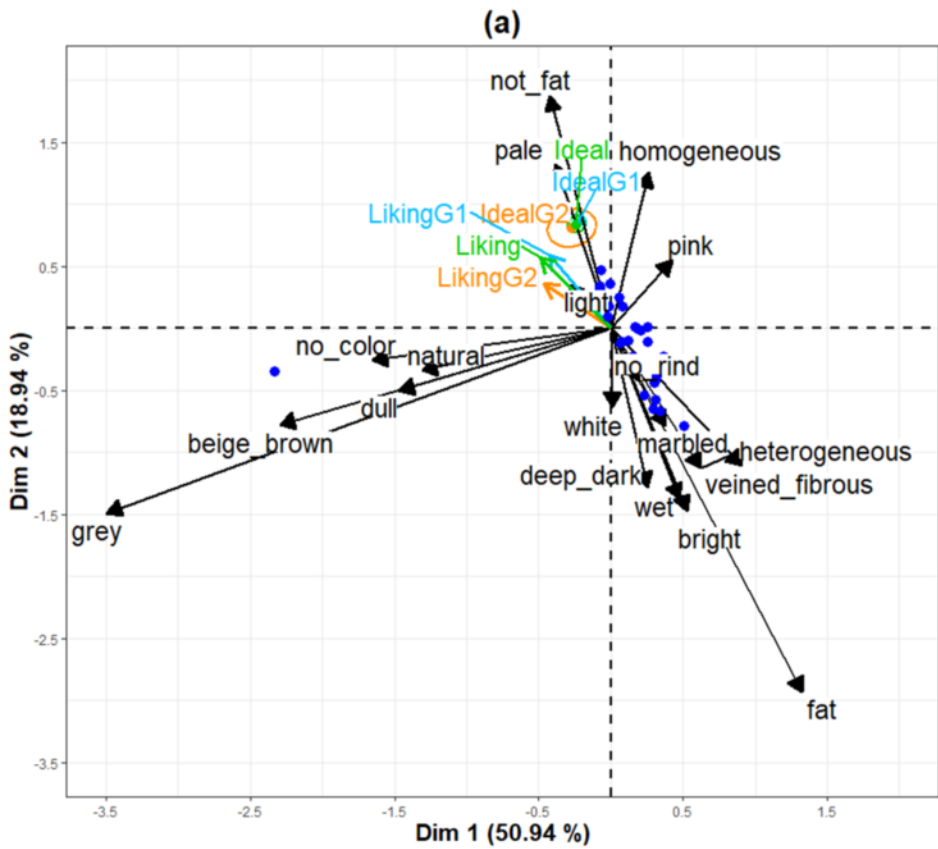
Fig. 3: Biplot from multiple-response Correspondence Analysis with the panel (Ideal) and by segment (IdealG1 and IdealG2) ideal products (projected as supplementary observation), their confidence ellipse ($\alpha = 5\%$) and the mean panel (Liking) and by segment (LikingG1 and LikingG2) liking scores (projected as supplementary variable): (a) axes 1-2 visual aspect, (b) axes 3-2 visual aspect, (c) axes 1-2 texture in mouth, (d) axes 3-2 texture in mouth, (e) axes 1-2 flavor, (f) axes 3-2 flavor. Blue points are the actual products (unlabeled for sake of readability). Weighted correlation values of liking scores can be read thanks to the axes ticks.

Fig. 4: Proportion of citations of descriptors mentioned in the FC descriptions of the ideal product within each segment with their respective confidence intervals ($\alpha = 5\%$).

Fig. 5: Regression loadings of each descriptor with their respective confidence intervals ($\alpha = 5\%$) for the two segments of consumers: (a) G1 (N = 351) and (b) G2 (N = 64). V stands for the visual descriptors, T stands for the texture in mouth descriptors and F stands for the flavor descriptors. Green (resp. red) bars represent significant ($\alpha = 5\%$) positive (resp. negative) drivers of liking.







Segment: 1 (N=351) 2 (N=64)

