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1 **Free JAR experiment: data analysis and comparison with JAR task**

2
3 *Alexiane LUC, Sébastien LE, Mathilde PHILIPPE, El Mostafa QANNARI, Evelyne VIGNEAU*

4
5 **ABSTRACT:**

6 The Free JAR protocol is introduced as a methodology for highlighting product improvement keys
7 without imposing specific attributes to the respondents. Being relatively new, there is a need to
8 demonstrate its relevance compared to an established sensory methodology such as the JAR
9 procedure. The first aim of this study is to outline a strategy for the statistical analysis of Free JAR
10 comments. This consists in extracting all the attributes assessed according to modalities such as "not
11 enough", "JAR" and "too much", and recoding the Free JAR comments of each respondent into a
12 products x attributes matrix. At a product level, an analysis is performed with the aim of highlighting
13 the attributes that characterize the product under study. Thereafter, a multivariate descriptive
14 analysis is presented. It consists in calculating a dissimilarity measure for each pair of products.
15 Multidimensional Scaling (MDS) is performed on the dissimilarity matrix thus formed in order to
16 obtain a graphical display that depicts the relationships among the products. For a comparison
17 purpose, the same analyses are applied to JAR data. The findings based on a case study pertaining to
18 cheeses make it possible to assess the respective shortcomings and benefits of Free JAR and JAR
19 procedures.

20
21 **KEYWORDS:** Free JAR; JAR; Free comment; Multidimensional scaling; Cheese

1. Introduction

In a product development context, R&D researchers aim to clearly identify consumers' expectations and perceptions as well as highlight product improvement keys in order to better monitor the R&D process. Various strategies, known as rapid methods of evaluation (Delarue, 2015; Valentin et al., 2012) are nowadays available to investigate such aspects. The common feature of these methods is that they are easy to understand by the consumers. In particular, we single-out the Just-about-Right (JAR) procedure. This method of evaluation has gained ground these last years and is particularly appropriate to highlight product improvement keys. Its relevance was demonstrated by several authors (Rothman and Parker, 2009; Popper, 2014). In this task, a panel of respondents, generally formed of regular consumers of the category of products under investigation, are instructed to assess a set of products on the basis of a list of predefined attributes. Typically, each attribute has three or five categories indicating intensity levels that range from "not intense enough" to "too intense", with the level "just about right" (JAR) as the mid-point (Popper, 2014). However, the fact that the list of attributes is predefined and is the same from one respondent to another is a limitation. Indeed, the list of attributes may be incomplete in that sense that key attributes may be overlooked, some attributes may not be relevant to all the consumers or may be differently interpreted from one consumer to another. Moreover, it was reported that presenting a list of attributes to the consumers could bias their evaluation in that it could bestow on some attributes much more importance than they actually deserve, making them the primary focus of the consumers (Ares et al., 2017; Lawrence et al., 2013; Popper et al., 2004).

To cope with these limitations, alternative strategies of evaluation such as the free comments procedure (ten Kleij and Musters, 2003) allow the consumers to freely express their perception of the products using their own words. The resulting description is very close to the consumers' mind and gives strength and value to their spontaneity. However, the resulting data are not satisfactory in a product development context since they lack a meaningful structure which would make them easily exploitable. Furthermore, it was reported that it is often difficult for the consumers to express themselves accurately and in an operational way to highlight product improvement keys (Lawless and Heymann, 2010; Symoneaux et al., 2012).

We developed a new method of evaluation called Free JAR (Luc et al., 2020) which stands as a compromise between the JAR procedure with a fixed list of attributes and the completely unconstrained expression of the consumers. In Free JAR, the consumers are free to use their own vocabulary to express their perception of the products but they are instructed to use a structure similar to that of the JAR procedure. This means that they are nudged to use such terms as "too much", "just about right" or "not enough". By so doing, Free JAR procedure aims to provide a structured verbalization of the products' improvement keys. However, although the data obtained by means of a Free JAR procedure are more structured than those obtained by means of a free comments procedure, their statistical treatment is quite challenging.

The Free JAR experiment yields two kinds of data: (i) categorization data, which convey hedonic information, and (ii) textual data subjected to have a JAR structure and which highlight the assets and weaknesses of the products. This paper complements the previous study (Luc et al., 2020), which was more concerned with the presentation of the Free JAR protocol and where the statistical data analysis was based on the hedonic categorization data only. In this paper, we discuss how to investigate the relationships among the products based on the assets and weaknesses highlighted by the respondents. Moreover, since Free JAR procedure is relatively new, there is still a need to demonstrate its relevance and its benefits compared to the JAR procedure.

The first aim of the study is to outline a strategy for the analysis of Free JAR data. This consists in recoding the Free JAR comments of each respondent into a *products x attributes* matrix. Thereafter, these matrices are submitted to *ad-hoc* statistical methods. The second aim of the study is to compare the findings from a Free JAR experiment to those from a JAR experiment and assess the respective merits and benefits of both tasks. The JAR experiment consists in evaluating a list of

73 predefined attributes according to JAR scales. For a straightforward comparison of the two methods
74 of evaluation, the same strategy of statistical analysis applied to Free JAR data is also applied to the
75 JAR data. To address these two issues, we set up a case study pertaining to cheese products whereby
76 a panel of consumers were randomly assigned to two sub-panels. The consumers of one sub-panel
77 were asked to perform the Free JAR task whereas the consumers of the other sub-panel performed a
78 JAR task on the same products.

79 The paper is organized as follows. In the first section, we give more details regarding the Free JAR
80 and JAR procedures, and we discuss how the data from these two protocols are analyzed. The data
81 collected for the comparison of these approaches are presented in a Case study section. The findings
82 are outlined in the section Results. Discussion and concluding remarks on the comparison of the two
83 methods of evaluation, namely JAR and Free JAR, are finally reported in light of the findings from the
84 case study.

85

86 **2. Data collection and statistical analyses**

87

88 **2.1. Comparison between Free JAR and JAR data collection**

89

90 The *Free JAR procedure* consists in two steps (Luc et al., 2020): (i) a categorization step, whereby
91 each respondent is instructed to sort the products into three hedonic categories, namely "I don't
92 like", "I like moderately" and "I like very much", (ii) an evaluation step whereby each respondent is
93 invited to freely express themselves on each of the products while encouraged to use the terms "too
94 much", "just about right (JAR)", "not enough" or equivalent phrasing. An example of Free JAR
95 comment is: "This product is too salty, not soft enough".

96 The first step aims at setting the respondent in a hedonic state of mind. In other words, it is used
97 as a nudge (Thaler and Sunstein, 2008) to make the respondent focus on which characteristics they
98 appreciate and which characteristics they do not appreciate in the products. In practice, this nudge
99 approach, discussed in more details in a previous paper (Luc et al., 2020), entails that a majority of
100 respondents express their assessments, in the second step, using a JAR structure. Sentence primers
101 are given to guide the respondents in their evaluation (Fig. 1).

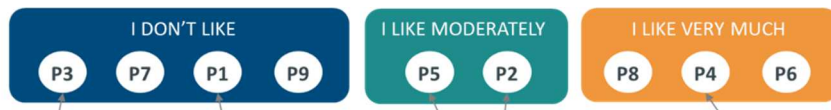
102 It is clear that unlike the JAR protocol where the respondents are asked to evaluate the products
103 based on a list of predefined attributes, the Free JAR protocol leaves the respondents free in their
104 choice of attributes used to describe each product. In particular, in the JAR procedure, the
105 respondents are instructed to assess the products according to all the attributes whereas, in the Free
106 JAR procedure, the respondents may use some attributes for some products and not for others.

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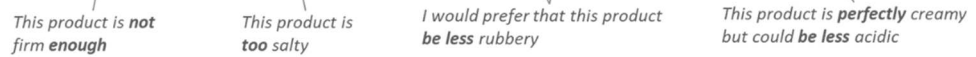
110 **STEP 1**
Categorization



112

113

114 **STEP 2**
Description with
JAR structuration



119

120 *Fig. 1: Summary of the Free JAR protocol*

121

122 **2.2. Analysis of the Free JAR and JAR data**

123

124 As stated above, an assessment given by a respondent after a preliminary hedonic categorization
125 should be focused on the products' assets and weaknesses. To achieve descriptive analyses, either at
126 a product level or for all the products combined, there is a need to carry out a preliminary textual
127 data processing. The goal is to extract, from the Free JAR comments, all the attributes associated
128 with a modality such as "too much", "JAR" or "not enough". For this purpose, a lexical analysis of
129 each Free JAR comment is carried out and all these attributes are collected in a table. Thereafter, a
130 grouping of synonymous terms is achieved. In practice, a few people (two or three) are involved to
131 carry out this lexical analysis and recoding in order to avoid as much bias of subjectivity as possible.
132 After having worked individually on a sample of comments from different respondents, a consensus
133 stage makes it possible to reach a detailed coding protocol of the sentences, which will be
134 implemented on the whole corpus.

135

134 For each respondent, an individual table is created: the rows correspond to the products and the
 135 columns correspond to the attributes used by the respondent to describe the products. For each of
 136 these attributes, the assessments are expressed by "too much", "just about right" or "not enough". In
 137 the following, we shall refer to these terms as "Free JAR modalities". Thus, for each respondent's
 138 table, we find, at the intersection of a row and a column, a Free JAR modality. As illustrated in Fig. 2,
 139 the values 1, 2 and 3 were assigned to the modalities "not enough", "JAR" and "too much",
 140 respectively. The data that are not available are indicated by the symbol "-". Obviously, several
 141 entries are not available because not all the attributes selected by each respondent apply to all the
 142 products. It is also important to note that from one respondent to another, the tables do not refer to
 143 the same attributes and, in particular, do not have the same number of columns.

Product	Attribute 1	Attribute 2	Attribute 3
P1	3	1	-
...			
P8	-	2	3

Fig. 2: Individual tables resulting from the recoding of the Free JAR comments

154 **2.2.1. Data analysis at a product level**

155
 156 We consider each product in turn. For each modality of each Free JAR attribute, we computed,
 157 on the one hand, the proportion of respondents who used this modality to describe the product
 158 under consideration and, on the other hand, the same proportion after pooling all the products.
 159 Thereafter, a hypothesis test based on the hypergeometric distribution (Lebart et al., 1995) was
 160 performed in order to assess whether the former proportion is larger than the latter proportion. This
 161 makes it possible to highlight which Free JAR attributes and which of their corresponding modalities
 162 specifically characterize the product under study.

164 **2.2.2. Multivariate descriptive analysis**

165
 166 In order to investigate the relationships among the products, the individual tables (Fig. 2) were
 167 horizontally concatenated, yielding a matrix that we denote by **X**. Obviously, the rows of this matrix
 168 correspond to the products and the columns correspond to the attributes elicited by all the
 169 respondents. In practice, each column of **X** is denoted by "attribute_ID of the judge that used it" (e.g.
 170 "salty_J1", to represent the attribute "salty" used by the judge J1). As stated above, several entries in
 171 **X** are missing because not all the attributes are used to evaluate all the products. Based on **X**, we
 172 undertake to calculate a dissimilarity measure between each pair of products, yielding a *products x*
 173 *products* dissimilarity matrix.

174
 175 The recoding of the Free JAR modalities into 3 categories, "1: not enough", "2: JAR" and "3: too
 176 much" is related to the fact that the distance between modalities "1: not enough" and "3: too much"
 177 is considered larger than that between modalities "1: not enough" and "2: JAR" and modalities "2:
 178 JAR" and "3: too much". Furthermore, the dissimilarity between each pair of products is computed by
 179 considering only the data from the Free JAR attributes that were used to describe both products.

180 Formally, the dissimilarity $D(i, i')$ between two products i and i' corresponds to the city-block
181 distance (Melter, 1987), also known as absolute value distance. It is given by:

$$182 \quad D(i, i') = \frac{1}{\text{Card}(A_{ii'})} \sum_{j \in A_{ii'}} |X[i, j] - X[i', j]| \quad (1)$$

184 where $A_{ii'}$ represents the set of columns in \mathbf{X} for which both products i and i' were assessed (i.e. the
185 set of Free JAR attributes used by the judges to assess both products), $\text{Card}(A_{ii'})$ is the number of
186 elements in $A_{ii'}$, and $\mathbf{X}[i, j]$ represents the entry of \mathbf{X} corresponding to product i and attribute j .

188
189 By way of investigating the relationships between the products, a metric Multidimensional
190 Scaling (MDS) was performed on the dissimilarity matrix \mathbf{D} . The aim is to seek a low-dimensional
191 representation space (ideally, a two-dimensional space) to depict the configuration of the products
192 with the requirement that the Euclidean distances between the products measured on this low
193 dimensional space should be as close as possible to the dissimilarities in matrix \mathbf{D} (Shepard, 1962). A
194 commonly used algorithm to achieve this goal is the SMACOF algorithm (De Leeuw and Heiser, 1977).
195 The number of axes for the representation space was chosen based on the stress criterion, which
196 reflects the lack of fit between the original dissimilarities and the Euclidean distances in the
197 representation space. Obviously, this criterion decreases as the number of axes increases. A rule of
198 thumb is that a stress value below 0.20 is acceptable (Cox & Cox, 1990; Kruskal, 1964).

199
200 As stated above, the aim of our study was also to compare the results of a Free JAR task with
201 those of a conventional JAR task. For this comparison purpose, the statistical procedure described for
202 the analysis of Free JAR data was applied to JAR data. In the case of JAR data, each individual data
203 table has the same number of columns since all the respondents use the same list of attributes.
204 Nevertheless, the data tables were also horizontally concatenated into a matrix \mathbf{X} . Thereafter, the
205 dissimilarity matrix between products was calculated using the same dissimilarity index as the one
206 defined in Eq. (1). In practice, for each pair of products (i, i') , $\text{Card}(A_{ii'})$ is equal to the number of
207 JAR attributes by the number of respondents. Eventually, the same Multidimensional Scaling
208 procedure was performed on the dissimilarity matrix thus computed.

209
210 The statistical analysis was performed within the software R, version 4.0.3 (R Core Team, 2020).
211 In particular, the FactoMineR package (Lê et al., 2008) version 2.4 and the smacof package (De Leeuw
212 and Mair, 2009) version 2.1 were used.

213

214 **3. Case study**

215

216 The data collection took place in downtown Bordeaux, France. Eight French pressed cheeses
 217 were assessed, including one cheese (Cantal) which was replicated (Table 1). These cheeses are
 218 among the most commonly available and commonly consumed pressed cheeses in France. All the
 219 cheeses were purchased at the same supermarket.

220

Cheese	Abbreviation	Cheese	Abbreviation
Beaufort	B	Emmental	E
Cantal	C	Morbier	M
Cantal (Replic.)	CR	Reblochon	R
Comte	CE	Saint Nectaire	S

221

222 *Table 1: The eight French cheeses used in the case study and their abbreviations*

223

224 A panel of 149 respondents took part in the experiment. They were recruited in the street by a
 225 team of investigators. They claimed to be regular consumers of pressed cheeses. Among these
 226 respondents, 43% were male and 57% were female. They were aged between 18 and 76 years.

227 The panelists were randomly allocated to two sub-panels. A sub-panel composed of 77 of the
 228 respondents participated in a Free JAR protocol, whereas the remaining 72 respondents evaluated
 229 the cheeses according to a JAR protocol. The eight products were presented in the form of cubes of
 230 dimensions 1 x 1 x 1.5 cm on a tray. They were arranged according to a balanced experimental
 231 design in order to avoid carry-over effect. Moreover, each respondent has neutral crackers and Evian
 232 water in order to neutralize their palate after tasting each cheese sample.

233

234 The nine predefined attributes used during the JAR protocol are given in Table 2, with their
 235 extreme anchors. These attributes are commonly used to describe cheeses in the studies conducted
 236 by the company that collaborated to this case study. They draw from the cheese sensory analysis grid
 237 available on the French dairy products website (at <https://www.produits-laitiers.com>). For the
 238 statistical analysis, the data were recoded as a three-point scale.

239

Attribute	Extreme anchors	Abbreviation
Color	"too yellow" to "too white"	color
Touch consistency	"too soft" to "too hard"	cons_touch
Smell intensity	"not intense enough" to "too intense"	smell
Taste intensity	"too bland" to "too intense"	intensity
Taste fruitiness	"not fruity enough" to "too fruity"	fruity
Taste salinity	"not salty enough" to "too salty"	salty
Texture firmness	"too soft" to "too firm"	firm
Texture creaminess	"not creamy enough" to "too creamy"	creamy
After-taste intensity	"not intense enough" to "too intense"	at_intensity

240

241 *Table 2: Nine attributes used in the JAR experiment*

242

243 **4. Results**

244

245 4.1. Analysis of Free JAR data

246

247 4.1.1. Preliminary data analyses

248

249 In a first place, we report that one hedonic categorization and six Free JAR comments were
250 missing.

251

252 The respondents used an average of 13 words to describe each product. However, this number
253 significantly varied from one respondent to another since some of them used up to 34 words to
254 describe a product, whereas others used only one word.

255 The number of times the modalities "too much", "JAR" and "not enough" have been used in Free
256 JAR task, broken down according to the three hedonic categories, is plotted in Fig. 3. It is clear that
257 the description of the products appears to be consistent with the hedonic categorization since the
258 modality "JAR" is highly associated with the category "I like very much", whereas the modalities "too
259 much" and "not enough" are more associated with the other two categories.

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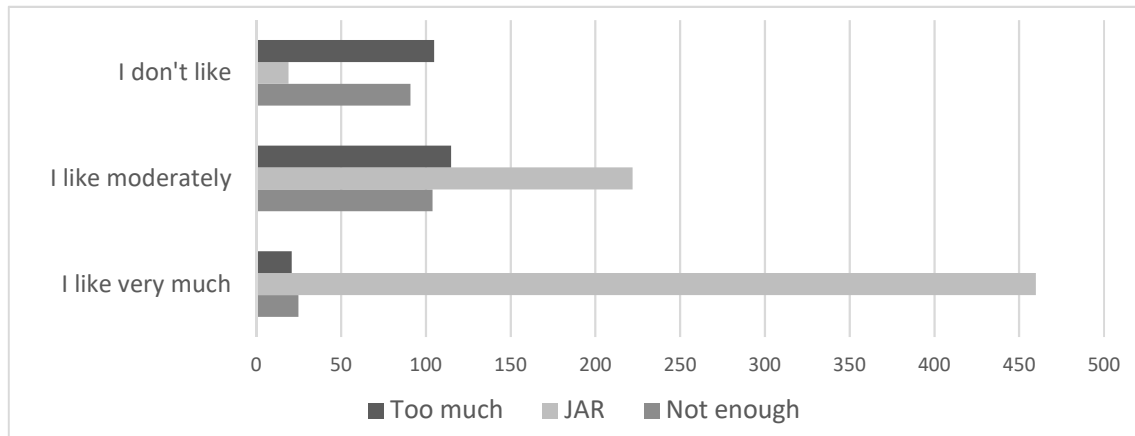
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273 Fig. 2: Number of times each Free JAR modality ("too much", "JAR" and "not enough") was used to describe the products for
274 each hedonic category.

275

276 4.1.2. Recoding of the Free JAR data

277

278 In a first stage, we carried out a lexical analysis for each Free JAR comment, as discussed in
279 Section 2.2. Then, a grouping of synonymous terms was realized: from an initial list of 253 extracted
280 attributes derived from the Free JAR comments, the grouping of synonymous terms yielded 51 Free
281 JAR attributes. As an example, grouping the terms *soft* and *tender*, on the one hand, and the terms
282 *firm*, *thick* and *hard*, on the other hand, led to the creation of a Free JAR attribute relative to the
283 firmness of the cheese. Each Free JAR attribute used in a comment is associated with a modality,
284 which is, in the example above: "too soft", "just about right" or "too firm". As explained in section
285 2.2., three people were involved in performing this recoding. More precisely, each one of them
286 worked individually on nearly 20 Free JAR comments before discussion with the other analysts with
287 the aim of setting up of a common recoding strategy. Eventually, the individual tables were
288 constructed with as many columns as attributes used to describe the eight cheeses. An example of
289 such a table is given in Fig. 4.

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For one respondent:

Product	Hedonic category	Description
B	I like moderately	I like it, but the taste is a bit strong.
CE	I like very much	I really like this cheese because it's just right salty, and the texture is perfect.
...		
S	I don't like	I don't like it because the cheese is too creamy and therefore the texture is too smooth.



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Product	Hedonic category	Intensity of the taste	Salty	Global texture	Creamy of the texture	Smooth of the texture
B	I like moderately	3	-	-	-	-
CE	I like very much	-	2	2	-	-
...						
S	I don't like	-	-	-	3	3

Fig. 3 : Transformation of the Free JAR data for one respondent into an individual data table. The symbol "-" indicates missing data.

309

It turned out that more than 93.5% of the respondents used at least one Free JAR attribute to describe the eight products. On average, there were seven Free JAR attributes used per respondent (Fig. 5).

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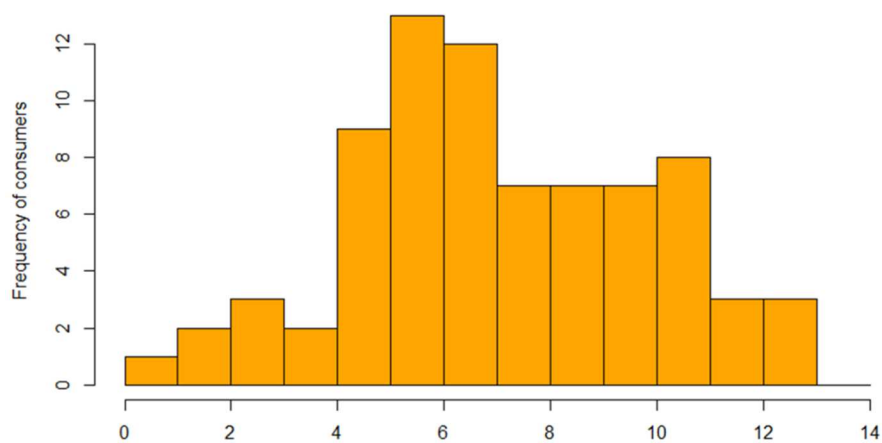


Fig. 4: Number of different Free JAR attributes used by the respondents

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The contingency table that cross-tabulates the attributes and the Free JAR modalities is built (data not shown to save space). This contingency table highlights the fact that some attributes are only used in association with some modalities and not with others. This is the case of those attributes with a negative connotation such as "after-taste acidic", "taste butter" or "cardboard texture", which are associated with the modality "too much" only. Contrariwise, some attributes are only assessed as "JAR", but never as "too much" or "not enough". This is the case for the attributes "fruity", "after-taste intensity" and "smell".

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We also created a contingency table that cross-tabulates the attributes and products in order to highlight those attributes that are used for specific products, and attributes that are used for several products (data not shown to save space). It turned out that ten attributes were specific to some products. These are mainly specific attributes such as the "overall Emmental taste", which refer to

338 the type of the products. Contrariwise, fifteen attributes were used to assess all the eight products.
 339 They are common attributes such as "intensity of the taste" or "firmness of the texture".

340
 341

342 Table 3 shows the most cited attributes, with a frequency of citation larger than 5%, among the
 343 51 Free JAR attributes. A first finding is that some of these attributes are also present in the
 344 predefined list used in the JAR test ("Taste intensity", "Texture firmness", "Texture creaminess" and
 345 "Taste salinity"). Most importantly, the Free JAR analysis highlighted attributes that we had not
 346 thought of for the JAR study, but which turned out to be important for the respondents. This is the
 347 case of the concept of "cheese character", which was cited by around 12% of the respondents.
 348 Contrariwise, some attributes that we thought were important and that were included in the
 349 predefined list of JAR attributes turned out to be not so important for the respondents. Examples of
 350 such attributes are the smell of the cheese or its fruity taste, which were cited by only 4.5% and 2.4%
 351 of the respondents, respectively.

352

Free JAR attribute	Frequency of use	Example
Intensity	37.01%	"The taste is too strong"
Overall texture	21.43%	"Very pleasant texture, I love it"
Overall taste	21.10%	"The taste is perfect"
Firm	15.58%	"The texture is too hard, I don't like"
Character	11.69%	"This product lacks character"
Overall appreciation	9.09%	"I like this cheese because it is pleasant"
Creamy	7.47%	"I don't like it because the texture is too dry"
Fluid	5.52%	"I find the texture of the cheese too liquid for me"
Salty	5.03 %	"This cheese is too salty"

353

354 *Table 3: Most cited Free JAR attributes based on the Free JAR comments*

355

356 4.1.3. Data analysis at a product level

357

358 As stated in Section 2.2.1, for each product in turn, we performed a hypothesis test to assess
 359 whether the frequency of citations of each modality of each Free JAR attribute for the product under
 360 consideration was larger than the same frequency for all the products combined. The most
 361 significant modalities, ranked by decreasing order of significance, are given in Table 4.

362

363

Product	Attribute	Level	% of citations for the product	% of citations all products	p-value
B	fruity	jar	3.9	1.2	0.011
	comte	jar	2.0	0.4	0.036
	acidic	too much	2.6	0.9	0.063
	character	too much	2.0	0.5	0.065
C	salty	too much	5.4	1.0	<0.001
	tx_common	not enough	1.4	0.3	0.087
	creamy	not enough	4.1	1.9	0.098

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CR	salty	too much	3.0	1.0	0.076
	intensity	not enough	19.0	8.7	<0.001
CE	overall_at	too much	3.0	0.6	0.008
	tx_common	too much	2.3	0.4	0.024
	emmental	jar	2.8	0.3	<0.001
	intensity	not enough	17.0	8.7	<0.001
	gruyere	jar	2.8	0.4	0.002
E	common	jar	2.1	0.3	0.013
	common	too much	2.8	0.7	0.020
	rubbery	too much	4.3	1.5	0.023
	overall_taste	not enough	2.1	0.4	0.029
M	at_intensity	jar	3.8	0.9	0.003
	firm	not enough	5.6	2.7	0.038
	firm	not enough	7.3	2.7	0.002
	sticky	too much	4.0	0.9	0.002
R	character	jar	7.9	3.7	0.012
	flowing	jar	5.3	2.2	0.027
	creamy	jar	4.0	1.7	0.071
	bitter	jar	1.3	0.3	0.092

Table 4: Characterization of the products by comparison of the frequencies of citations for Free JAR data (tx: texture; at: after-taste)

Examples of conclusion that can be drawn from Table 4 are: (i) both the Cantal cheeses (C and CR) appear to have a too pronounced salty taste; (ii) the Comte and the Emmental cheeses seem to be too common and too bland; (iii) the Reblochon cheese is perceived as too sticky and not firm enough.

4.1.4. Multivariate descriptive analysis

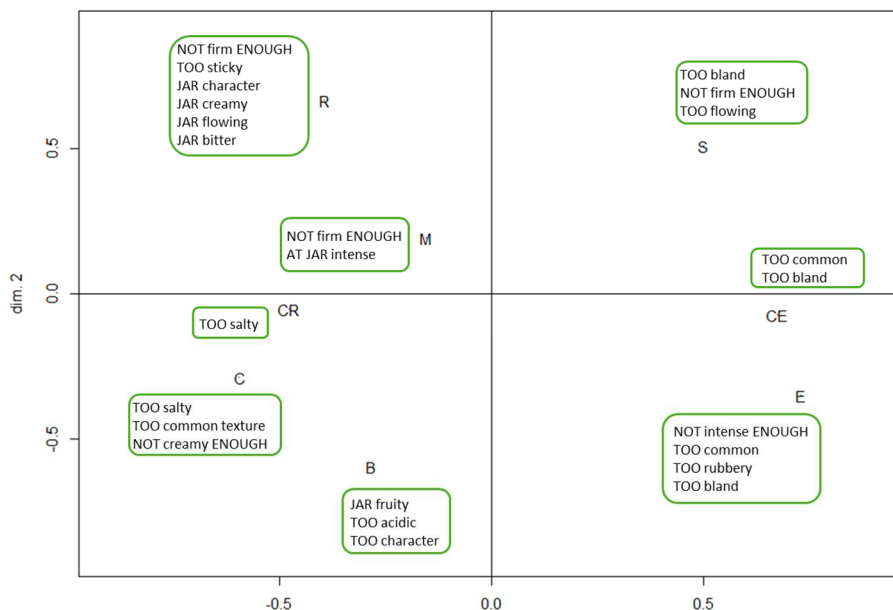
From the 77 concatenated individual tables, which give the assessment of the eight products based on the Free JAR attributes, we computed a *products x products* dissimilarity matrix based on Eq. (1) (Table 5). We also show in this table the number of instances (i.e., assessments) that served to compute each dissimilarity measure.

	B	C	CE	CR	E	M	R	S
B	0	0.24 (51)	0.39 (36)	0.33 (46)	0.58 (38)	0.27 (49)	0.50 (40)	0.60 (37)
C	0.24 (51)	0	0.59 (39)	0.15 (41)	0.54 (37)	0.31 (42)	0.46 (37)	0.47 (43)
CE	0.39 (36)	0.59 (39)	0	0.39 (39)	0.19 (36)	0.51 (37)	0.58 (38)	0.24 (41)
CR	0.33 (46)	0.15 (41)	0.39 (39)	0	0.41 (34)	0.35 (37)	0.23 (31)	0.58 (33)
E	0.58 (38)	0.54 (37)	0.19 (36)	0.41 (34)	0	0.44 (41)	0.66 (32)	0.37 (38)
M	0.27 (49)	0.31 (42)	0.51 (37)	0.35 (37)	0.44 (41)	0	0.31 (39)	0.37 (43)
R	0.50 (40)	0.46 (37)	0.58 (38)	0.23 (31)	0.66 (32)	0.31 (39)	0	0.33 (55)
S	0.60 (37)	0.47 (43)	0.24 (41)	0.58 (33)	0.37 (38)	0.37 (43)	0.33 (55)	0

Table 5: Product dissimilarity matrix based on the Free JAR data. In bold, the smallest and largest dissimilarities are highlighted. Between parentheses, the number of instances that were used to compute each dissimilarity measure are indicated.

397 It appears that the smallest dissimilarity is between the repeated Cantal samples. We can
 398 observe that the Emmental and the Comte cheeses are close to each other. Contrariwise, the largest
 399 dissimilarity is between the Emmental and the Reblochon cheeses. The Saint-Nectaire and the
 400 Beaufort cheeses are also far removed from each other.

401
 402 The dissimilarity matrix was submitted to the MDS procedure. We chose a two-dimensional
 403 representation of the products, which corresponds to a stress value of 0.18. The product
 404 representation, based on these two first dimensions, is shown in Fig. 6. On this graphical display, we
 405 superimposed the characterization of the products extracted from Table 4.



423 *Figure 5: Final representation of Free JAR results*

425 We can see that the first MDS axis opposes the Cantal cheeses (C and CR), the Morbier (M), the
 426 Beaufort (B) and the Reblochon (R) cheeses, characterized by a strong intensity, to the Emmental (E),
 427 the Comte (CE) and the Saint-Nectaire (S) cheeses, characterized by a bland and common aspect. The
 428 second axis opposes the Reblochon (R) and Saint-Nectaire (S) cheeses, characterized by a flowing and
 429 not firm enough texture, to the Emmental (E) cheese, characterized by a rubbery texture, and the
 430 Beaufort (B) and Cantal (C) cheeses, characterized by an under-representation of the use of the "not
 431 firm enough" attribute.

432
 433 **4.2. Analysis of JAR data**

434
 435 **4.2.1. Data analysis at a product level**

436
 437 Based on the contingency table that cross-tabulates the eight products and the nine assessed
 438 attributes, a description of frequencies is carried out, in order to highlight the JAR modalities that are
 439 more often used to describe a product rather than the others. The attributes together with their
 440 modalities are ranked by decreasing order of significance. The most significant ones are shown in
 441 Table 6. They are named according to the abbreviations defined in Table 2.

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Product	Attribute	Level	% of citations for the product	% of citations all products	p-value
B	cons_touch	too much	3.7	2.0	0.004
	intensity	jar	6.8	4.7	0.014
	color	too much	3.9	2.5	0.026
C	salty	too much	5.7	2.7	<0.001
	cons_touch	too much	4.6	2.0	<0.001
	intensity	too much	3.7	2.3	0.022
CR	firm	jar	8.3	6.2	0.027
	salty	too much	5.6	2.7	<0.001
	firm	too much	3.2	1.8	0.009
CE	color	not enough	5.1	1.9	<0.001
	intensity	not enough	6.6	4.1	0.001
	cons_touch	jar	7.9	5.7	0.016
E	creamy	not enough	4.5	2.5	0.002
	intensity	not enough	6.3	4.1	0.005
	cons_touch	jar	8.0	5.7	0.01
	salty	not enough	4.3	2.8	0.019
M	firm	too much	3.1	1.8	0.019
	smell	too much	3.5	1.2	<0.001
	at_intensity	too much	5.1	2.4	<0.001
	intensity	too much	4.9	2.3	<0.001
	cons_touch	not enough	6.5	3.4	<0.001
R	firm	not enough	5.9	3.1	<0.001
	creamy	too much	4.8	2.7	0.001
	cons_touch	not enough	9.4	3.4	<0.001
	firm	not enough	8.2	3.1	<0.001
	creamy	too much	7.3	2.7	<0.001
S	color	too much	4.6	2.5	0.001
	cons_touch	not enough	7.7	3.4	<0.001
	firm	not enough	6.5	3.1	<0.001
	color	too much	5.4	2.5	<0.001
	at_intensity	not enough	7.1	4.0	<0.001
	creamy	too much	5.2	2.7	<0.001
	intensity	not enough	7.1	4.1	<0.001
salty	not enough	5.2	2.8	<0.001	
smell	not enough	7.3	4.6	0.002	

Table 6: Characterization of the products by comparison of the frequencies of citations for JAR data (at: after-taste)

Examples of conclusion that can be drawn from this table are: (i) both the Cantal cheeses (C and CR) appear to have a too pronounced salty taste; (ii) the Comte and the Emmental cheeses appear to be not intense enough; (iii) the Morbier cheese seems to be too intense; (iv) the Reblochon and the Saint-Nectaire cheeses seem to be too soft and not firm enough.

4.2.2. Multivariate descriptive analysis

Once the information regarding the assets and weaknesses of the various products is highlighted, we aim to graphically represent these products in order to investigate their relationships. As proposed in Section 2.2.2, a dissimilarity measure based on Eq. (1) is calculated for each pair of products from the matrix \mathbf{X} that concatenates all the individual JAR assessments. In this case, all the attributes were assessed by all the respondents for all the products. The resulting dissimilarity matrix is presented in Table 7.

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	B	C	CE	CR	E	M	R	S
B	0	0.58	0.70	0.59	0.68	0.79	1.06	0.99
C	0.58	0	0.70	0.49	0.73	0.86	1.08	1.01
CE	0.70	0.70	0	0.66	0.61	0.90	1.05	0.87
CR	0.59	0.49	0.66	0	0.68	0.79	1.06	0.97
E	0.68	0.73	0.61	0.68	0	0.90	1.08	0.85
M	0.79	0.86	0.90	0.79	0.90	0	0.86	0.92
R	1.06	1.08	1.05	1.06	1.08	0.86	0	0.73
S	0.99	1.01	0.87	0.97	0.85	0.92	0.73	0

Table 7: Product dissimilarity matrix based on the JAR data. In bold, the smallest and largest dissimilarities are highlighted.

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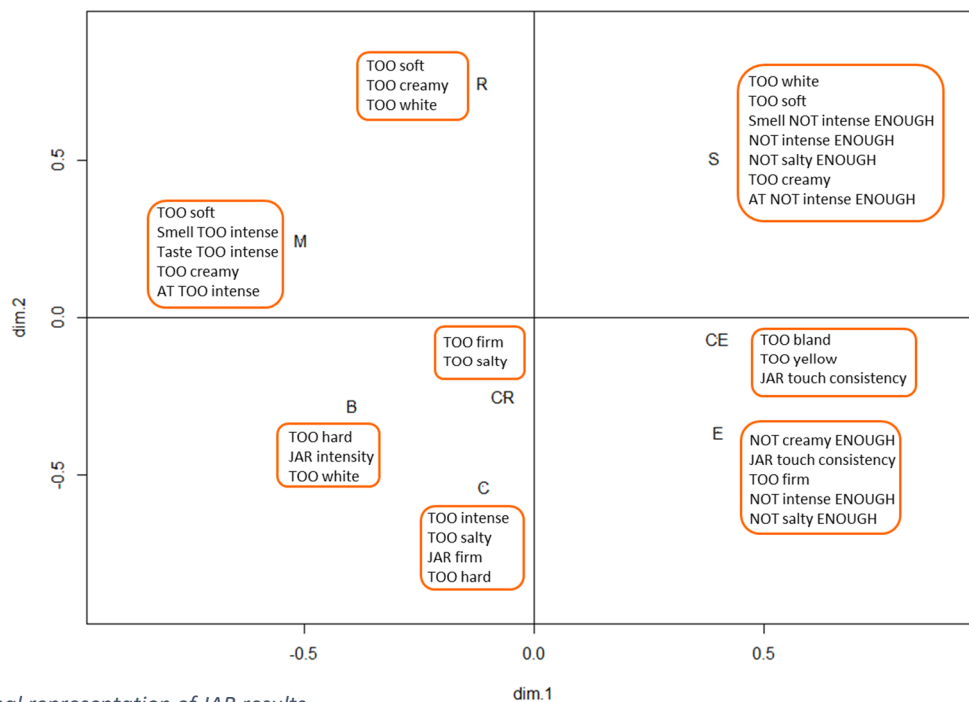


Fig. 6: Final representation of JAR results

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This graphical representation of the products highlights the same oppositions on both axes as the Free JAR representation. In particular, the first axis opposes the Morbier (M), the Beaufort (B), the Cantal (C and CR) and the Reblochon (R) cheeses, characterized by a strong intensity, to the Comte (CE), the Emmental (E) and the Saint-Nectaire (S) cheeses, characterized as bland cheeses. The

538 second axis opposes the Reblochon (R), the Saint-Nectaire (S) and the Morbier (M) cheeses,
539 characterized by a soft texture, to the other cheeses, which appear firmer.

540 **5. Discussion and concluding remarks**

541
542 The two MDS representations of the products in Fig. 6 and Fig. 7, respectively associated to Free
543 JAR and JAR experiments, bear similarities to each other. This is also supported by the RV coefficient
544 between the two configurations, which is equal to 0.68. Indeed, in both configurations, the Comte
545 (CE) and the Emmental (E) cheeses are close to each other, and so are the Reblochon (R) and the
546 Saint-Nectaire (S) cheeses. Moreover, the Cantal (C) cheese, which was replicated in order to assess
547 the repeatability of the respondents, is close to its replicate (CR) in both figures.

548 In terms of product improvement keys highlighted by both procedures of evaluation, several
549 concordant conclusions can be drawn. For instance, the Cantal cheese is perceived as too salty and
550 not creamy enough, the Comte cheese is perceived as too bland and the Reblochon cheese, too
551 creamy. However, some findings were evidenced by the Free JAR approach, and not by the JAR
552 experiment. This can be explained by the fact that in this latter task we used a restricted predefined
553 list of attributes. For example, Free JAR data reveals that the Reblochon is too sticky and just about
554 right in terms of cheese character. Another example concerns the Emmental, which is perceived as
555 too common and too rubbery. It is noticeable that more attributes emerge as significantly
556 differentiating the products from JAR data than from Free JAR data. This is due to the fact that the
557 number of citations per attribute and per product is higher for each JAR modality than for each Free
558 JAR modality. These higher citation frequencies must be related to two main reasons: in the JAR
559 procedure, the number of attributes to assess is limited and all these attributes are evaluated by all
560 the respondents.

561 It is worth noting that the Free JAR procedure makes it possible to highlight the relative
562 importance of the used attributes, which is a very valuable information. In particular, it highlights the
563 fact that the taste intensity is the most cited attribute in Free JAR comments, ahead of the firmness
564 attribute.

565 Another noteworthy finding is that the attribute "character of the cheese" emerged as an
566 important attribute in the Free JAR, whereas this attribute was not present in the predefined JAR list.
567 The term "character" is defined as "the typical or original aspect of something" (Larousse, n.d.). In
568 sensory analysis of cheeses, it could be assimilated to the taste intensity of the products. A closer
569 examination of the comments where the term "character" was used indicates that this term is
570 connected to "unique", "special", "original" or "typical". It was related in only 30% of the instances to
571 the taste intensity of the cheeses. Thus, although the character aspect of a cheese is to some extent
572 linked to its intensity, it fundamentally reflects a different kind of perception.

573
574 Overall, the two procedures of evaluation (i.e., Free JAR and JAR) seems to point to the same
575 improvement keys, which validates the proof of concept as to the Free JAR procedure. As a matter of
576 fact, the free comments are steered towards highlighting the products' assets and weaknesses
577 through a nudge strategy whereby the respondents are instructed to sort the products in three
578 hedonic categories. The paramount advantage of the Free JAR task is its flexibility since the
579 respondents are free to use their own vocabulary to assess the products and are not constrained to
580 use a predefined list of attributes, that they may not clearly understand or may interpret differently
581 from one participant to another (Coulon-Leroy et al., 2017; Kim et al., 2017). As a consequence, the
582 attributes and improvement keys that might be overlooked by using a JAR test can be revealed by
583 performing a Free JAR experiment. Moreover, the importance of these findings can be inferred from
584 the respondent's comments (e.g., frequency of citations).

585 One may argue that the list of attributes in a JAR experiment could be improved and made more
586 comprehensive by setting up preliminary experiments (e.g., focus groups, repertory grid analysis).
587 Besides the cost and effort incurred by such preliminary investigations, there is still the risk that
588 these attributes might be interpreted differently from one respondent to another. Thus, the Free JAR
589 procedure better fulfills the requirements of a rapid method of sensory evaluation that meets the
590 expectations of market research institutes.

591 Instead of a Free JAR experiment, one may think of an alternative task akin to Free choice
592 profiling (Arnold & Williams, 1986; Williams & Langron, 1984) whereby each respondent generates,
593 in a first step, their list of attributes. Then, in a second step, they assess the products according to
594 this list, following the Free JAR steps. In other words, each respondent has their own list of attributes
595 but, unlike Free JAR task, all the attributes of this list are used to assess all the products. Obviously,
596 this alternative task is more time consuming and, more importantly, the respondents' evaluations
597 would be less spontaneous than in a Free JAR experiment, as discussed herein. Moreover, Free JAR
598 task is much more convenient than this alternative task in studies where respondents are picked at
599 random in the street or during exhibitions. Indeed, setting up a list of attributes, be it common to all
600 the respondents or specific to each respondent, entails presenting a relatively large set of products
601 to the assessors to stimulate their imagination in the elicitation process.

602 Another noteworthy remark is that JAR and Free JAR could complement each other. The Free JAR
603 procedure could be used to generate insightful attributes. For routine experiments, these attributes
604 could be used in JAR experiments. The complementarity of the two tasks is backed up by the fact
605 that they use the same kind of scales.

606 Notwithstanding its merits, a limitation to the use of the Free JAR procedure needs to be
607 stressed. The recoding of the Free JAR data appears very time-consuming since the Free JAR
608 comments are considered in turn and interpreted in terms of JAR evaluations. For the cheese case
609 study, it took the three analysts around three hours and a half to achieve this task. Further
610 investigations are needed in view of automating this lexical approach. We believe that Natural
611 Language Processing (NLP) (Bird et al., 2009; Silge and Robinson, 2017) and machine learning
612 algorithms (Ribeiro et al., 2016) could help tackling this issue.

613 Future work will also focus on how to better assess the dissimilarities among the products based
614 on the Free JAR data. In particular, we are investigating how to interpret the fact that some
615 respondents used a given attribute to assess a specific product and not the other products.

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617
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