

**1 PermAnova testing and Poisson Log-Normal modeling unravel how two traditional cheeses
2 are distinguished through sorting and verbalization tasks**

3 P-M Grollemund^a, L. Lenoir^b, J. Benoit^b, C. Chassard^b, C. Bord^b

4 ^aLaboratoire de Mathématiques Blaise Pascal (LMBP), Université Clermont Auvergne – IUT de
5 Clermont-Ferrand

6 ^bUniversité Clermont Auvergne, INRAE, VetAgro Sup, UMRIF, 63370 Lempdes, France
7

8 Corresponding author: Cécile Bord

9 cecile.bord@vetagro-sup.fr

10 VetAgro Sup, 89 avenue de l'Europe, 63370 Lempdes, France.

11

12

13 Highlights

- 14 • Three types of panel were selected to perform a sorting task on uncooked cheeses
- 15 • PermAnova testing and Poisson Log-Normal modeling identified key variables in a
16 verbalization task
- 17 • Poisson Log-Normal model shows value for analyzing counts data
- 18 • Verbalization is best explained by 'knowledge' × 'panel' variables

19

20 **Keywords:** PDO cheeses, Free sorting, Verbalization task, PLN model, PermAnova

21

22Abstract

23The aim of this study was to explore how two categories of uncooked cheeses (*Salers versus*
24Cantal) can be perceived differently according to how panelists sort them (free sorting task) and
25how they verbally describe them (verbalization task). We focused on determining the
26mechanisms underpinning the ability to distinguish the two cheeses by considering additional
27panelist information. Three types of panels (an expert panel, an intermediate panel and a novice
28panel) with different levels of cheese expertise performed a sorting task and a verbalization task
29on 10 cheeses. Data from the sorting task was analyzed using the DISTATIS method and data
30from the verbalization task was analyzed by using a basic correspondence analysis paired with an
31original approach mobilizing PermAnova and a Poisson Log-Normal (PLN) model.

32The results showed that the cheeses' configurations are similar except between the expert and
33intermediate panels. Overall, none of the panels clearly separated Cantal from Salers cheeses. In
34the verbalization task, different types of panel used different sets of terms to describe the
35categories. The expert panel preferentially used descriptive terms related to flavour whereas the
36intermediate and novice panels both tended to use quantitative (intensity) and hedonic terms.
37Knowledge of the product space under study was found to be the variable that best explains the
38terms used by each panel. PermAnova testing and PLN modeling emerged as novel approaches
39for identifying the key variables that explain the use of terms in the description task.

40

41 1. Introduction

42France offers a huge number of all kinds of cheeses, but only 45 of them have obtained a
43Protected Designation of Origin (PDO) label to promote the quality and protection of authentic
44regional products. PDO products are distinguished by traditional craft and singular sensory
45qualities based on adherence to strict production standards and specifications. Among the typical
46French PDO cheeses, Cantal and Salers are uncooked cheeses produced in the Massif Central

47area (France). The two cheeses are similar but not the same in appearance, and many consumers
48struggle to distinguish between them. However, experts confidently distinguish the two cheeses
49based on particular gustatory differences (Bérard et al., 2016). Salers and Cantal cheeses are two
50very distinct cheeses that differ on several points, from production process (conditions of cheese-
51making, ripening time) to the dairy systems used (milk origin, seasonal production, and so on)
52(Callon et al., 2005; Agabriel et al., 2004) that converge to shape the distinct and distinctive
53sensory properties of Cantal and Salers cheeses (Cornu et al., 2009).

54The sensory properties of various products can be measured using various descriptive sensory
55methods, such as sensory profiling (Meilgaard et al., 2015). Sensory profiling serves to describe
56specific qualities of a product and quantify them on a scale of intensity using a trained panel
57(*ISO 13299:2016*). However, there are faster alternative methods for obtaining a sensory map of
58products. Although popular in psychology, the free sorting method has largely developed in
59sensory analysis. It is a simple and relatively intuitive method in which participants freely group
60samples into subsets according to their similarities, and it can be used to assess a large set of both
61food and non-food products (Deegan et al., 2010; Merlo et al., 2022; Hollins et al., 1993;
62Giboreau et al., 2001). This method thus affords a perceptive representation of a set of samples.

63Data from sorting tasks is generally analyzed using multidimensional scaling (MDS). There are
64many methods similar to MDS, such as the DISTATIS method that combines classical MDS
65(Abdi et al., 2007) and STATIS that accounts for the variability of panelists (individual data).
66DISTATIS yields two types of maps: one for the panelists and one for the products. These maps
67correspond to data projections in a low-dimensional space computed such as to lose the least
68amount of information. The proximity between two points in the maps reflects a partial
69similarity, which means that these maps can be analyzed using the same rules as standard metric
70MDS or Principal Component Analysis (PCA).

71To give meaning to perceptive space, previous works suggest adding an optional step to a free
72sorting procedure by asking the panelists to verbalize, i.e. use terms to describe the groups
73formed (Cartier et al. 2006, Blancher et al. 2007). Faye et al. (2004) argued that the combination
74of categorization and description makes it possible to obtain explanations about the dimensions
75of the perceptual map. Even though this method looks simple to set up, several points of the
76methodology needed to be discussed, including the type of panel selected (trained/untrained
77panel) and the vocabulary used to describe the products. Several studies have compared trained
78and untrained panels on categorization tasks (Faye et al. 2004; Parr et al. 2010; Lelièvre et al.
792008). In the wine domain, these studies have shown that experts are able to categorize wines
80according to grape variety. Through repeated exposure to wines from different categories,
81experts develop a kind of prototypical or central tendency that represents a sensory signature of
82these categories (Honoré-Chedozeau et al., 2019). Other studies have shown that experts are
83better in terms of discrimination, memory and description. Despite this better discrimination and
84description by experts, MSD with naive panelists nevertheless leads to similar results regarding
85product positioning. However, some authors have reported that trained or expert panelists tend to
86be more efficient in their description, and other authors have shown that the vocabulary used by
87untrained or novices panelists can be ambiguous, redundant, and less specific than that the
88vocabulary verbalized by experts (Chollet & Valentin, 2001). Likewise, Lawless, Sheng &
89Knoops (1995) showed that expert panelists with a good knowledge of cheeses used a wide
90variety of meaningful descriptive terms compared to untrained panelists. Overall, it seems that
91knowledge and expertise play a role in how panelists describe products or utilize descriptor
92words.

93On the other hand, qualitative analysis of terms is still difficult to interpret due to the different
94semantics used and the variety of terms selected. Verbalization generates a great many terms,
95and so before an MDS method can be applied, it is often necessary to pre-process the

96verbalization data, which can be done by categorizing the terms by family (Chollet & Valentin,
972000; Soufflet et al., 2004). As pointed out by Chollet & Valentin (2001), the description of
98products can mobilize several dimensions (hedonic, qualitative, quantitative), but the emergence
99of these dimensions depends on the coherent product space.

100The dimensions of a product map can often be correlated with additional attributes to facilitate
101interpretation. The verbatim comments resulting from this categorization can then be analyzed
102by any of several methods, such as correspondence analysis which allows to project the cited
103terms on the map. However, other statistical methods could be used to better understand the use
104of word categories by experts/novices. In particular, the heterogeneity in verbalization can be
105reformulated as a hypothesis testing problem or a choice of model. In this context, permutational
106ANOVA (PermAnova) (Anderson, 2001, 2017) is a suitable tool. Moreover, using Bayesian
107Information Criterion(BIC) (Schwarz, 1978) to select a model from one of the various Poisson
108Log-Normal (PLN) regression models (Chiquet et al. 2021) is another suitable direction.

109To our knowledge, no studies have used a statistical approach based on PermAnova testing or
110PLN modeling to investigate the effect of types of panel on the categorization of French PDO
111cheeses and how panels use terms to describe cheeses according to their expertise. In this
112context, the objectives of this study were to (i) identify the perceptual representation of cheeses
113by panelists according to panel expertise level, and (ii) determine the difference in verbalization
114(use of word categories) by different panels using PermAnova and PLN modeling to find out
115which variables (knowledge, cheese type and cheese consumption) best explain the use of the
116terms by the different panels.

1172 **Material and methods**

1182.1 **Cheese samples**

119Two categories of cheeses were studied, i.e. Cantal (C) and Salers (S), which are specific PDO
120cheeses from the Auvergne region of France. For each category, cheeses were made with raw

121milk from either Salers (CSal/SSal) or other cow breeds (CR/SR). A total of ten cheeses were
122analyzed for this study (Table 1). All samples were stored in the same maturing cellar and were
123analyzed at 12 months of ripening. This process was implemented to precisely control the
124ripening conditions of all the cheeses. Whole cheeses (approximate weight of 40 kg) were
125selected directly in the maturing cellar by supply-chain professionals, and held in cold storage at
1261°C for one week prior to analysis.

127In order to be representative of the existing sensory diversity, three subsamples were selected for
128each of the stated categories of cheeses, except for CSal where a single subsample was analyzed.

129

1302.2 Panel selection

131Knowledge can be defined through two major components: familiarity and expertise. Iba &
132Hutchinson (1987) defined familiarity the number of product-related experiences the consumers
133have accumulated. More recently, Nacef et al. (2019) confirmed the different definitions of
134familiarity as related to product knowledge, experience with the product or the purchase, and
135consumption of the product. Expertise is defined as the ability to successfully perform product-
136related tasks. According to Chi, Feltovich & Glaser (1981), expertise is domain-specific and can
137be used to describe skills, knowledge or abilities in tasks, jobs, games or sports. In this case,
138‘expert panel’ is not associated to sensory experts as defined in the ISO standards on sensory
139testing but to professional experience with cheese. Three sets of panelists were recruited:

- 140 • **an expert panel (n = 18)** including cheese-making professionals (farmer, cheese-maker,
141 laboratory technician, cheese engineer or scientist) located around the cheese production
142 area. In this case, experts (such as oenologists, brewers, cheese-makers, etc.) use their
143 technical knowledge-sets.

- 144 • **an intermediate panel (n= 10)** including people working at Rungis market (a bastion of
145 French gastronomic heritage and a well-known landmark in the gastronomic landscape),
146 specifically people engaged in dairy sales, such as wholesalers or market operators.
- 147 • **a novice panel (n =44)** including cheese consumers living around the city of Clermont-
148 Ferrand (familiar novices who regularly eat Cantal and/or Salers cheeses).

149 Participants were given questionnaire including items on socio-demographics (age, gender and
150 professional activity) and tasting and consumption habits. To be selected for the consumer panel,
151 consumers had to routinely consume Salers or Cantal cheeses and be over 18 years old. Informed
152 consent was obtained from each participant. Table 2 describes the panels.

153

154 2.3 Experimental design

155 2.3.1 Free sorting and verbalization task

156 Different sessions were set up over three weeks, but each panelist only participated in a single
157 1.5-hour session. The sessions took place in different French cities according to panel type
158 (expert panel: Aurillac and Lyon; intermediate panel: Rungis (Paris); novice consumer panel:
159 Clermont-Ferrand). The sessions were organized in a room that was amenable to tasting (not a
160 sensory laboratory) while adhering to the conditions required for sensory tests.

161 Panelists received a full set of cheese samples. A randomized plan gave the order for sample
162 presentation. Three cubes of cheeses (2×2×2 cm) were cut and placed in a plastic cup. All
163 cheeses were presented in three-digit numbers and served at room temperature (20°C±1°).

164 The panelists were asked to look at, smell, and taste each cheese sample to sort them into groups
165 of cheeses based on sensory similarities. No criteria were provided to perform the sorting task.
166 Number of groups and number of samples per group were free, as were the criteria for grouping
167 the samples, which could vary from panelist to panelist. However, at least two groups had to be
168 formed, and each cheese sample had to be selected once into a group. After the sorting task, the

169panelists were asked to describe each group of cheeses using words (no sentences). Panelists
170were provided with mineral water and unsalted crackers to cleanse their palate between samples.

171

172**2.3.2 Knowledge questionnaire**

173A questionnaire was designed to assess the panelists' knowledge on cheese and validate their
174membership group. This questionnaire was split into two parts: (1) 13 questions related to their
175overall knowledge on cheese, (2) 12 specific questions about cheese-making process for Salers
176and Cantal cheeses. As the correct answer was known for each question, individual responses
177were coded 0 for a wrong response and 1 for a correct one. This questionnaire was filled out at
178the end of the tasting session, and was scored out of 20 points. A global knowledge index was
179obtained by computing a weighted mean of specific knowledge (weight: 0.7) and overall
180knowledge (weight: 0.3).

181

182**2.4 Data analysis**

183**2.4.1 Analysis of the free sorting task**

184For each panelist, we built an individual distance matrix using the discrete metric from the
185results of the sorting task, for which the rows and the columns are cheese samples. Specifically, a
186value of 0 for the j -th element of the i -th line of the matrix indicates that the corresponding
187panelist pools the i -th and the j -th cheese samples together, whereas a value of 1 indicates that
188the samples were not put together. In this context, the dataset is a collection of individual
189distance matrixes on which an MDS method is usually used to derive sensory maps (Blancher et
190al., 2007). Here we used the DISTATIS method to analyze the individual distance matrixes
191obtained from the sorting data. DISTATIS method is an extension of classical multidimensional
192scaling taking into account individual sorting data (Abdi et al., 2007).

193

194

15

16

1952.4.2 Analysis of the verbalization task

196To facilitate the interpretation of the graphical displays obtained by MDS, the terms cited by
197panelists are superimposed by considering their correlations with the MDS axes. For each
198panelist, the terms are suggested to describe a given category of stimuli are assumed to apply to
199every single stimulus in that category. Very often, it becomes necessary to pre-process data from
200the verbalization task. Indeed, panelists generally generate a large number of separate terms,
201which can prove time-consuming to graph out. For instance, terms that are deemed to be
202synonymous or share a common meaning should be merged and identified as the same word.
203Sometimes, terms that are only cited by a few panelists generally get discarded.
204Here, to properly encode each term used, we draw up a list of categories ready to integrate each
205term into a category prior to any data analysis. We chose to establish 9 categories to provide
206balanced and interpretable categories:

- 207 • Taste: all terms describing taste or intensity of perceived taste
- 208 • Texture: all terms describing texture (in-mouth or to-touch)
- 209 • Appearance: all terms describing appearance (core or rind)
- 210 • Odour intensity: all terms in relation to intensity of odour (quantitative terms)
- 211 • Flavour intensity: all terms in relation with intensity of flavour (quantitative terms)
- 212 • Odour-descriptive: all terms in relation with odour description (qualitative terms)
- 213 • Flavour-descriptive: all terms in relation with flavour description (qualitative terms)
- 214 • Liking: all terms describing preference, hedonic perception (liking or disliking)
- 215 • Typicality: all terms in relation to the perception of typicality (belonging to a given category
216 of cheese, connected with the terroir or the ripening process)

217In addition to a descriptive analysis performed via an MDS approach, a major objective of this
218study is to identify whether panelists' verbalizations depend on type of panel or on type of

219cheese to. Two approaches are investigated to test these potential links: a PermAnova test and a
220PLN model.

221PermAnova is a non-parametric statistical test. Here, to evaluate the link between the type of
222panelists and their verbalizations, the null hypothesis corresponds to similar verbalization among
223panels in terms of mean and variance. Calculating the statistic involves computing the pairwise
224distances between all individual data. Given that verbalization data consists of vectors of count
225data, we choose to measure the proximity between two vectors using Bray-Curtis dissimilarity
226(Bray & Curtis, 1957). In this study, PermAnova is used to jointly test whether type of panel and
227type of cheeses resulted in a difference in verbalizations. Each p-value obtained is considered a
228measure of support for the null hypothesis, in line with recent scholarship on statistical
229significance (McShane et al., 2019).

230As an alternative approach, the PLN method involves modeling the individual verbalization
231counts as a Poisson random variable for which the log rate has a prior individual-specific
232Gaussian distribution. Assuming an individual-specific prior distribution makes it possible to
233model potential heterogeneity in the intensity of verbalization across panelists. Moreover, adding
234regression terms to the prior Gaussian expectation leads to express the intensity of verbalization
235as a linear combination of dependent factors such as type of panel, panelist knowledge, and type
236of cheese. Here, we compared several PLN models with different regression terms to deduce
237which factors explain an important share of the variance in verbalization. Choice of model was
238based on BIC. The robustness of the proposed analysis was evaluated with a bootstrap
239procedure.

240

2413. Results

2423.1 Analysis of the free sorting task

2433.1.1 Cheese configuration for each panel

244Figure 1 shows the DISTATIS compromise maps of the 10 cheeses for each panel. Overall, we
245found slight differences in configuration between the types of panel, as confirmed by the values
246of the RV coefficient computed between the configurations of different panels. Configurations
247are globally similar between novice/expert (RV = 0.622, p = 0.007) and between
248novice/intermediate (RV = 0.525, p = 0.04) but are dissimilar between expert/intermediate (RV=
2490.435; p = 0.153). None of the panels were able to distinguish between Cantal and Salers cheeses
250but all panels formed the same number of cheese categories, i.e. three groups, although there are
251differences between the groups identified.

252For the novice panel, the first dimension (accounting for 32.57% of variance) opposed three
253Cantal cheeses (CR4, CR5, CR6) and two Salers cheeses (SSal7, SR10) against other cheeses,
254while the second dimension had two groups separating “SSal9/Csal3/SR12” from “SSal8/SR11”.
255The small confidence intervals reflect good agreement among panelists.

256In the categorization performed by the intermediate panel, there is no clear opposition between
257cheeses and a greater overlap between confidence intervals, indicating weak agreement among
258panelists. The first dimension opposed Salers cheeses (SSal7, SSal8, SSal9, SR10) against a
259group composed of two Cantal cheese (CR5 and CR6) and one Salers cheese (SR11). the second
260dimension featured one group formed by three samples (SR12, CR4 and CSA13).

261In the categorization by the expert panel, the first dimension (accounting for 34.86% of variance)
262opposes four Salers cheeses (SR11, SR12, SSal8 and SSal9) against other cheeses composed of
263four Cantal cheeses (CR5, CR6, CR4 and CSal3) and two Salers cheeses (SR10 and SSal7). Like
264the novice panel, the small confidence intervals reflect good agreement among panelists.

265

2663.1.2 DISTATIS robustness analysis

267The numerical and graphical DISTATIS results point to two main interpretations. First, the
268intermediate panel appears to be significantly different to the expert panel in terms of cheese

269categorization. Second, the confidence ellipsis appeared to be larger for the intermediate panel
270compared to other panels (Figure 1). Note however that these interpretations may again be due to
271the small sample size of the intermediate panel. Below we address both these issues using
272bootstrapping and subsampling methods.

273For the expert/intermediate RV coefficient, we randomly subsampled the expert panel and
274computed the 'subsamped expert'/intermediate RV coefficient to obtain the same sample size
275for both panels and then evaluate how far sample size distinguished the intermediate and expert
276panels. We repeat the process 1000 times to obtain i) the proportion of p values greater than 0.01
277and ii) the position of the original RV coefficient value (RV= 0.435) with respect to the
278empirical distribution of the RV coefficient under expert panel subsampling. There are 99.2% of
279p-value greater than 0.01, and the original RV coefficient corresponds to the 73.5%-quantile of
280the empirical RV distribution. Subsampling the expert panel has no effect on the difference
281between intermediate and expert panels: the two panels are significantly different in all cases.

282To analyze the radius of the ellipsis for each panel, we compute the average rate between radius
283of ellipsis of the intermediate panel and the expert panel (resp. novice panel), i.e. 2.131 (resp.
2841.465). As above, we randomly subsampled the expert and novice panels in order to obtain
285panels with an even sample size, then we repeated the subsampling method 1000 times to obtain
286the overall average rate between radius of ellipsis, i.e. 1.283 for the expert panel and 1.203 for
287the novice panel. Having a reduced panel sample size substantially decreased the radius of
288ellipsis, especially for the expert panel. Moreover, the original average rate corresponds to an
289extreme value of the empirical distribution of the average rate under subsampled panels, which
290also indicates that panel sample size drastically affects ellipsis radius. Nevertheless, even though
291the small panel sample size contributes to the ellipsis radius, the subsampled expert panel always
292led to a greater average ellipsis radius than the intermediate panel and in 99.9% of cases led to a
293greater average ellipsis radius than the novice panel. Furthermore, empirical distributions (for

294 subsampled expert and novice panels) did not support the hypothesis that average ellipsis radius
295 rate is even across panels, since it did not cover the value 1. Even though a smaller sample size
296 increased the ellipsis radius, the intermediate panel still had larger ellipsis.

297

298 **3.2 Analysis of the verbalization task**

299 **3.2.1 Main differences between panels**

300 In this study, the panelists across all three panels used a total of 455 different words. Figure 2
301 represents the average frequency of the terms cited for each panel. Bigger balloon size reflects
302 greater use of the term by the panel. Correspondence Analysis highlights across-panel
303 differences in use of descriptive terms (Figure 3), which is confirmed by a Chi-squared test ($p <$
304 2.2×10^{-16}). The first principal component (89.9% of total inertia) contrasts the expert panel and
305 other panels. The expert panel is strongly associated with descriptive terms (Odour-descriptive
306 and Flavour-descriptive) whereas panelists from the intermediate panel preferentially refer to
307 terms related to enjoyment of the eating experience (Liking). The second principal component
308 (10.2% of total inertia) mainly differentiated the intermediate vs novice panels. Although the
309 novice panel is also associated with the Liking category, it is specifically related to other
310 categories on sensation intensity (Odour intensity and Flavour intensity) and more particularly
311 terms describing the visuals of the products (Appearance).

312 The on-average difference between panels can be evaluated by computing a contingency table
313 then running a Chi-squared test and correspondence analysis. Intra-panel inertia can also be
314 analyzed in order to measure the intensity of the split between panels.

315 **3.2.2 PermAnova-based differences in verbalization**

316 To compare panels on differences in product description, PermAnova is used as a non-
317 parametric statistical test. Only pairwise distances between panelists are required to assess
318 whether or not panels differed in terms of average and dispersion. Since each panelist's data is a

319vector of word category counts, the distances between two panelists are computed according to
320Bray-Curtis dissimilarity. We find that the panels differed in verbalizations, whether in terms of
321average, dispersion or both ($p = 0.001$). PCA analysis is performed on the verbalizations table
322(Figure 4a) to identify whether average or dispersion (or both) differed across panels. According
323to the PCA results, only dispersion differs between panels.

324The same process as above is also used to investigate differences in verbalization per type of
325cheese evaluated, i.e. Cantal vs Salers. The PermAnova test confirms a difference ($p = 0.0051$),
326which is also the case when jointly considering cheeses and panels (panel factor p -value =
3270.0001 and cheese factor p -value = 0.0032). PCA analysis (Figure 4b) indicates that averaged
328verbalization does not differ between types of cheese but that there is slightly higher dispersion
329in verbalization around Salers.

330For the type of panel and/or type of cheese factors, the PermAnova test finds significant
331differences that translate as a combination of differences in terms of average and especially
332dispersion.

333**3.2.3 Probabilistic modeling to assess panel differences**

334An alternative approach to assess verbalization differences between panels and or types of
335cheese is to formulate the question as a choice of model. We model vectors of counts, as
336abundance data, with a multivariate Poisson distribution for which the log-intensity is assumed
337to be Gaussian (Chiquet et al. (2021)). The regression terms can be considered to relate
338heterogeneity in verbalization to independent variables, such as a panel variable that indicates
339which panel each vector data refers to. We test models that only included an intercept, or a panel
340regression term, or a product regression term, or panel and product regression terms, and so on
341for all the available independent variables.

342The fitted models are compared based on BIC, and we use a bootstrap procedure to evaluate
343whether or not observed differences in BIC significantly diverged from to differences in BIC

344obtained from augmented models under additional pure random variable. Figure 5 shows that
345including panel factors in a PLN model induces a clear improvement in BIC, whereas the cheese
346factor does not appear relevant for explaining heterogeneity in verbalization, which means that
347the panelists generally fail to differentiate Salers from Cantal cheeses.

348**3.3 Knowledge and verbalization**

349Expert knowledge on cheese is mainly a key factor to drive verbalization heterogeneity among
350expert panel. Figure 5 shows that there is a hierarchical order of knowledge among the panels.

351Here, the three groups that we formed essentially on the basis of their experience and expertise
352with cheese were validated by their scores on the knowledge test. The expert panelists scored
353highest on overall knowledge and had similar scores to other panelists on both knowledge of
354cheese in general (Figure 5a) and more specific knowledge on Salers cheese (Figure 5b).

355Conversely, the novice panelists scored lowest on aggregate knowledge (9.5/20), with low scores
356for specific knowledge on Salers cheese and an intermediate score of 14.5 for knowledge on
357cheese in general, which is not significantly different to the intermediate panel.

358According to the BIC (Figure 6), the PLN regression model that best explained the intensities of
359the categories verbalized was the model that factored in the knowledge and panel variables. The
360increase in BIC after adding a regression term related to the knowledge factor supports an
361influence of this knowledge on verbalization. Each type of knowledge has a similar BIC gain,
362which seems to indicate that either the types are highly correlated or their differences are not
363significant in terms of explaining panelists' verbalizations.

364Moreover, the fact that the interaction of knowledge and panel variables leads to the best model
365of the diversity in verbalization across panelists means that:

- 366 • the panel variable alone is not sufficient, and that intra-panel diversity in knowledge has
367 to be addressed as a key factor, and

368 • the knowledge variable alone is not sufficient, which means that two panelists who have
369 roughly the same knowledge score but are in different panels might use different terms to
370 describe cheese.

371 Table 3 illustrates an assessment of the average contribution of each variable for the best PLN
372 regression model according to type of panel and panel knowledge. More specifically, it gives the
373 average terms per panel, variable-by-variable, in the latent regression model predicting log
374 intensity in the Poisson model of verbalization data. Positive (resp. negative) value indicate that
375 the focal variable positively (resp. negatively) affects intensity of usage of that word-category.
376 To facilitate interpretation, contributions of the 'Salers knowledge' variable are distributed
377 across the different panels, as knowledge differs significantly from panel to panel ($p < 0.001$ for
378 each pairwise panel comparison).

379

380 **4. Discussion**

381 **4.1 Sorting task and terms used during the verbalization task**

382 First, the categorization carried out on the 10 cheeses showed that even though some products
383 were not grouped together, all between-panel configurations except expert/intermediate were
384 fairly similar, but not identical. Overall, these results are in line with the literature on other
385 products (Lawless & Glatter, 1990). For instance, Faye et al. (2013) found that
386 configurations/sorting on wine glasses differed according to subject experience and knowledge.
387 The second objective of this study was to unravel the difference in use of the terms cited during a
388 verbalization task. Several studies have shown that the combination of free sorting and verbal
389 description leads to a perceptual map with explainable dimensions (Popper & Heymann, 1996).
390 Several authors have shown that the dimensions of MDS configurations resulting from
391 evaluation by untrained panelists can be interpreted using the vocabulary generated (Chollet &
392 Valentin, 2000, Lim & Lawless, 2005, Lawless, 1989, Lawless et al., 1995). Giboreau et al

393(2001) showed that perceptual maps on different fabric samples were relatively similar between
394trained and untrained panelists. However, other authors have shown that descriptions produced
395by untrained panelists are not always comparable to descriptions produced by expert subjects, as
396trained/expert panelists tend to be more efficient in their description. Lawless, Sheng & Knoops
397(1995) found that many of the descriptors used are significant but that experts use a wider variety
398of significant terms than untrained subjects. Furthermore, trained panelists use a more precise
399vocabulary as attributes generated by consumers are more ambiguous or redundant and less
400specific than attributes assigned by experts (Chollet & Valentin, 2001; Chollet & Valentin,
4012006). In this study, we observe a similar pattern: after gathering the terms into word categories,
402we find that the expert panel has more words that are related to qualitative terms and therefore
403more specific, whereas the novice/intermediate panels used more terms related to pleasure
404(hedonic), product appearance, and intensity descriptors. Lawless et al. (1995) applied this same
405method on cheese samples and showed that the results were similar between trained and
406untrained panels, but the trained group had a greater number of significant attributes when
407regressed with the MDS space.

408In the literature, several studies converge to agree that overall, experts present a more technical
409and specific vocabulary and they have the most extensive vocabulary than novices. These studies
410have mainly been conducted in the wine and beer sector (Chollet & Valentin, 2000; Gawel,
4111997; Lelièvre et al., 2009).The superiority of the experts' vocabulary is due to the addition of
412technical and specific terms on top of the basic novice vocabulary, as reported in the extant
413literature. Indeed, several studies have shown the effect of expertise (knowledge) on the
414description of products. For instance, Lelièvre (2010) showed that beer professionals and beer
415connoisseurs perceived beer according to sensory, hedonic and technical properties whereas non-
416connoisseurs mainly structured their perceptions on the basis of sensory attributes. Likewise,
417Faye et al. (2013) showed that description and sorting on wine glasses were influenced by

418panelists' knowledge and experience and their engagement with the products. Note, however,
419that they grouped their experts/non-connoisseurs post-hoc, whereas here we defined our
420expert/intermediate/novice panels beforehand. Even if frequency of consumption features in the
421definition of familiarity and plays a role in knowledge of a product, as mentioned by Nacef on
422Maroilles cheese, the utilization of terms here was not dependent on frequency of Salers
423consumption and this variable did not improve the PLN model.

424

425**4.2 Relevance of PermAnova and PLN modeling for the purpose of verbalization analysis**

426The novel statistical approach employed provided key insight into which variables drive the use
427of different terms for describing the products. We showed that different types of panels can
428produce similar perceptual maps but that the sorting and especially the word categories used
429depend on the panelists' expertise and knowledge of the product. These results confirm those
430already illustrated in the literature, but the combination of PermAnova testing and PLN modeling
431offers a powerful new way to analyze data resulting from free sorting task and verbalization
432tasks.

433PermAnova makes it possible to distinguish several levels of differences in verbalization.
434Graphical checking via PCA analysis can be used to determine whether verbalization data differ
435in average, in dispersion, or both. However, it would be instructive for future work to quantify
436the contribution of each component, i.e. average differences and dispersion differences, towards
437rejecting the null hypothesis.

438PLN modeling brings a new way to study the variables that contribute to the use of word
439categories by panelists and thus better understand the mechanisms involved in perception in
440interaction with panelist knowledge as an experimental factor, as suggested by Faye et al. (2013).
441This approach makes it possible to capture which factors impact verbalization and, crucially, to
442determine the intensity and direction of the association. However, further developments can be

443envisaged for this PLN model. In particular, it may be useful to adopt a variable selection
444approach (regularized estimators) or to define a suitable prior in a hierarchical Bayesian model
445(spike-and-slab) in order to more robustly identify the relevant factors that explain differences in
446verbalization among panelists. In addition, the PLN model, which is used more in the field of
447ecology (Chiquet, Mariadassou & Robin, 2021) has received recent gained broader attention, and
448extensions have already been proposed. For instance, Zero-inflated PLN allows to model counts
449data with a large amount of zeros in the database. In the context of verbalization analysis, this
450approach could make it possible to analyze verbalization data without necessarily having to
451resort to creating word categories.

452

453**4.3 Limitations and directions for future work**

454Concerning the limits of our study, the size of the panels might be a weakness that could have an
455impact on the validity of the results. The panels used had different sizes depending on the type of
456panelists recruited or their training, and were relatively small, at between 10 and 20 panelists
457(Soufflet et al., 2004) when panelists are considered as professionals/experts. In contrast, the size
458is larger (ranges from 9 to 300) when panelists are untrained or naive consumers (Cadoret et al.,
4592009; Moussaoui & Varela, 2010; Varela & Ares, 2012, 2012). According to Faye et al. (2006),
460the number of consumers really necessary to perform the free sorting task may be small (here, 25
461consumers still seems acceptable). However, we addressed the small sample size issue and we
462provided insights that support the results reported.

463Regarding the verbatims, we did not study the loss of information according to number of
464consumers, but the number of terms increases with number of consumers and thus occurrences of
465the terms. The fact that we used representative consumer terms makes the explanation of the
466perceptive configuration robust, and the number of consumers recruited in this study enabled us
467to collect a large number of words.

468

469 **5. Conclusion**

470The free sorting method followed by a verbalization task on 10 uncooked Cantal/Salers pressed
471cheeses revealed consistent configurations across different types of panels, except between the
472expert/intermediate panels. Overall, statistical analysis does not find a clear separation between
473Cantal and Salers cheeses, even in expert panel. Analysis of verbalization based on a combined
474PermAnova and PLN model approach highlighted that verbalization was differentiated according
475to type of panel. Furthermore, this approach showed that the ‘cheese’ variable did not appear to
476be a driving factor in panelist verbalizations. This indicates that panel verbalizations were not
477based on the nature of the cheese (Cantal or Salers) but rather on the ‘knowledge’ variable. This
478insight enabled us to more accurately model the verbalization data, and learn that the ‘knowledge
479× panel’ variables interaction better explained panelists’ verbalizations or use of word categories.
480The PLN model method offers an informative way to analyze counts data, particularly from
481verbalization, and brings supplementary information to help better understand which variables
482best explain the choice of terms used by different panels.

483

484**Table**

485Table 1: Description of the cheese samples

Cheeses	Type of milk	Producer / Dairy	Cheese samples (code)
Cantal	Salers milk	Dairy 1	Csal3
Cantal	Other cow breed milk	Dairy 1	CR4
Cantal		Producer 1	CR5
Cantal		Producer 2	CR6
Salers	Salers milk	Producer 3	SSal7
Salers		Producer 4	SSal8
Salers		Producer 5	SSal9
Salers	Other cow breed milk	Producer 6	SR10
Salers		Producer 7	SR11
Salers		Producer 8	SR12

486

487Table 2: Key characteristics of each panel

Cheeses	Modality	Expert (n =18)	Intermediate (n =10)	Novice (n =44)
Cheese_overall consumption	Several times/day	47.1	40.0	20.5
	1 time/day	29.4	10.0	36.4
	1 to 6 times/week	23.5	30.0	40.9
	2 to 3 times/month	0	10.0	2.3
	Never	0	10.0	0
Cantal_Consumption	Every day	5.9	0.0	4.5
	1 to 6 times/week	29.4	20.0	38.6
	1 to 3 times/week	47.1	40.0	47.7
	Never	17.6	40.0	9.1
Salers_Consumption	Every day	11.8	0.0	0.0
	1 to 6 times/week	47.1	30.0	15.9
	1 to 3 times/week	29.4	20.0	70.4
	Never	11.8	50.0	1.6
Gender	Male	72	80	39
	Female	28	20	61
Age	19-29	18	0	12
	30-45	29	50	23
	46-59	35	50	23
	> 60	18	0	42
School level	Secondary	17	20	45
	Undergraduate	56	40	33
	Masters	28	10	21
Marital Status	Single	17	20	18
	Married/Partner	83	80	59
	Separated	0	0	23

488

489

490

491

492

41

42

493 Table 3: Average contribution of each word category to the best PLN regression model according
 494 to type of panel and type of knowledge

Word_category	Novice_ panel	Intermediate_ panel	Expert_ panel	Novice _S_knowledge	Intermediate _S_knowledge	Expert_ S_knowledge
Liking	0.4467 ¹	0.1457	-0.5554	0.2280	0.3412	0.4719
Appearance	-1.4833	-2.6582	-61.6768	0.7876	1.1783	1.6299
Flavour_descriptive	0.9489	-0.1606	3.0391	-0.9029	-1.3507	-1.8685
Flavour_intensity	0.7114	0.0519	-0.3581	0.0495	0.0741	0.1025
Typicity_concept	-0.7774	-1.2107	-0.1999	-0.2934	-0.4390	-0.6072
Texture	1.2508	0.8734	0.9832	0.0054	0.0081	0.0112
Taste	0.0350	-1.7041	0.8985	-0.3165	-0.4734	-0.6549
Odour_intensity	-0.4077	-1.4491	-0.5852	-0.5024	-0.7516	-1.0397
Odour_descriptive	-1.2857	-59.2474	-1.1911	-0.2896	-0.4332	-0.5993

495 S= Salers; ¹Contribution expressed in log intensity

496

497

498

499

500

501

502

503

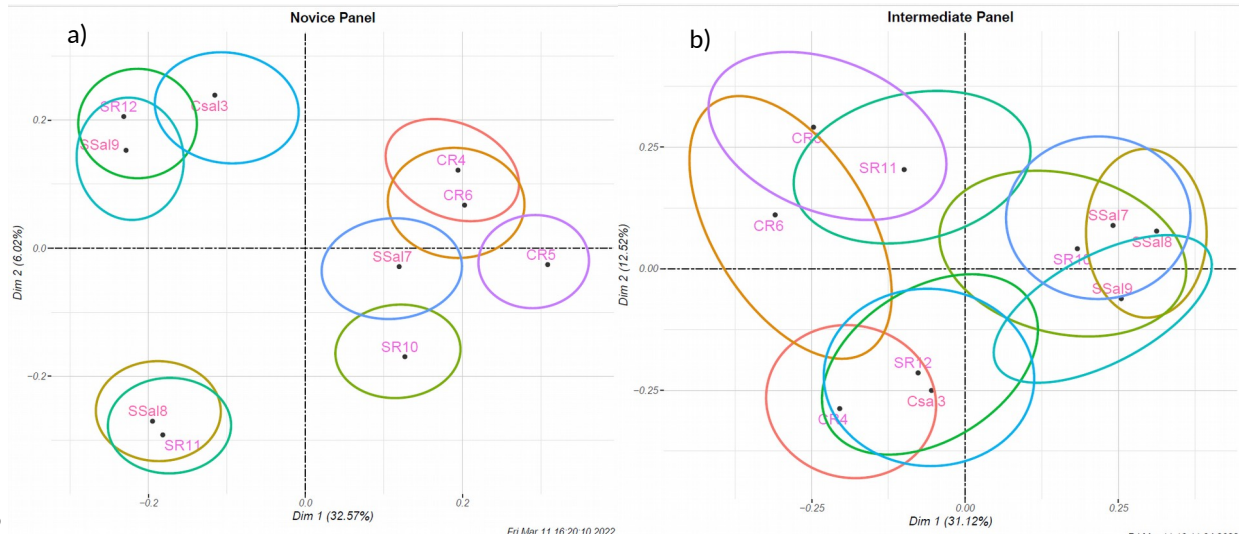
504

505

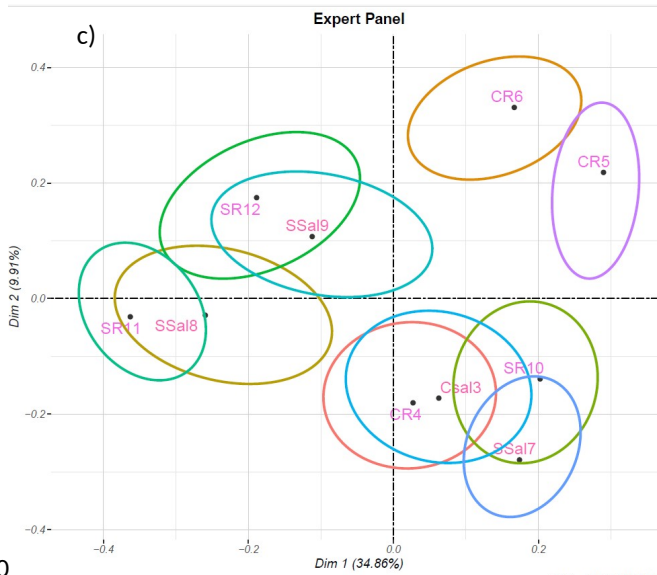
506

507

508**Figures**



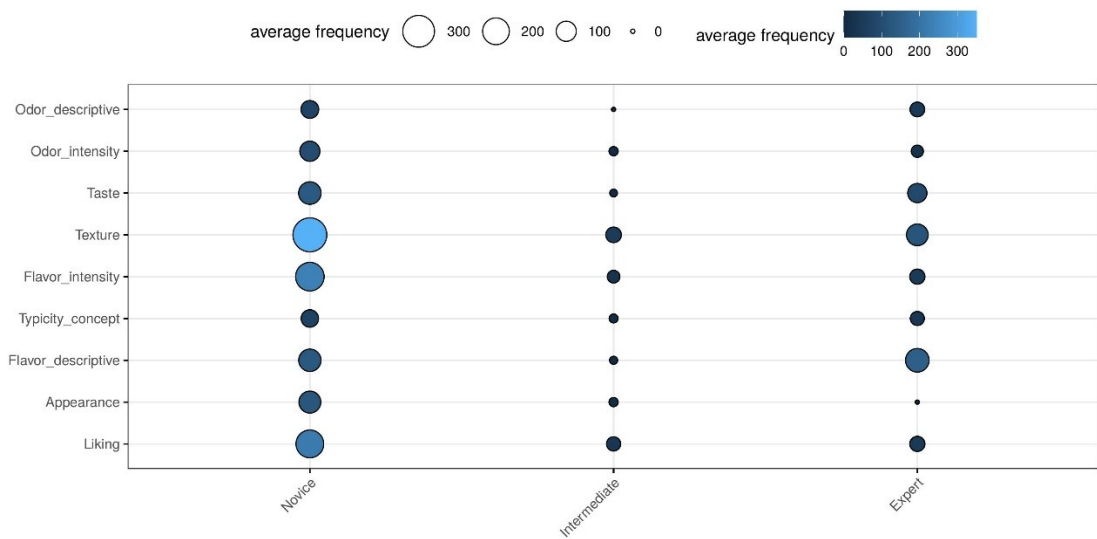
509



510

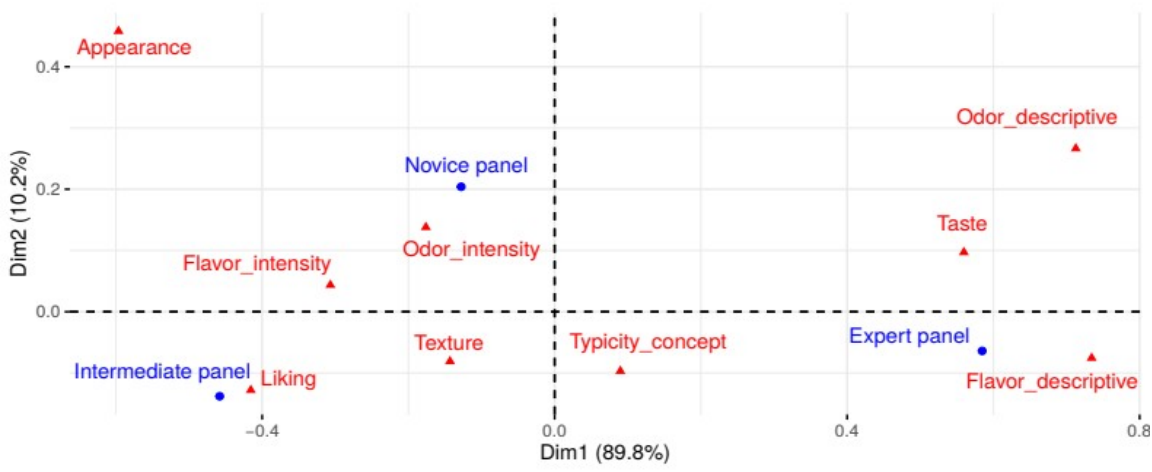
511**Figure 1: DISTATIS compromise maps of the ten cheeses with 95% confidence ellipses (Dim1-Dim2) for each**
 512**panel: a) Novice panel (n= 44); b) Intermediate panel (n=10); c) Expert panel (n=18)**

513



Fig

ure 2: Balloon plot representing the average frequency of the terms cited for each panel

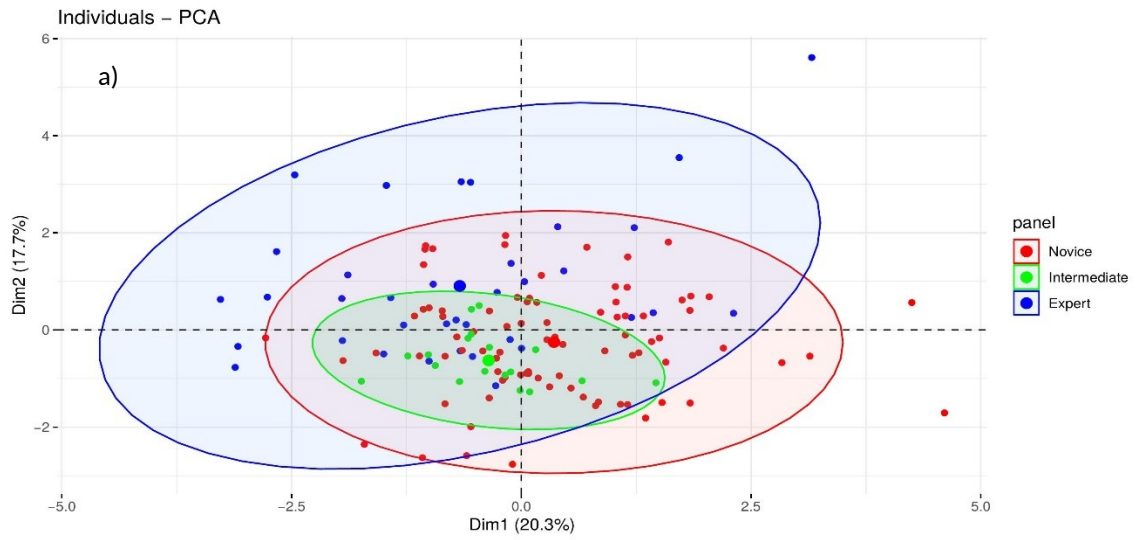


514
515
516
517
518
519
520
521
522
523
524
525

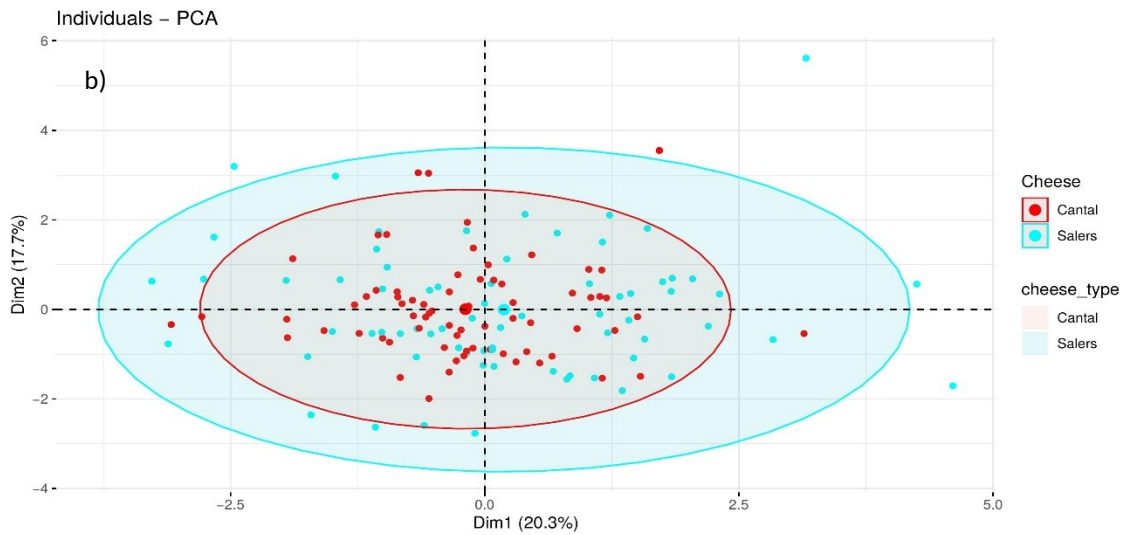
526Figure

5273: Plot from the correspondence Analysis between types of panel and cheese descriptor terms used

528



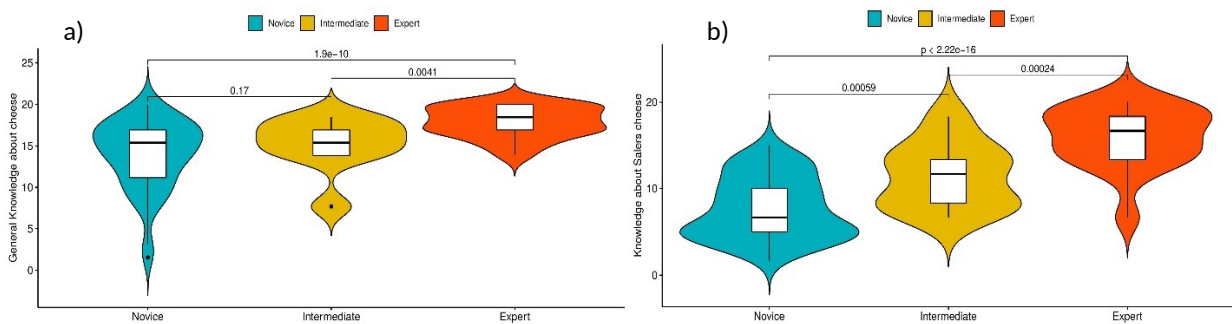
529



530

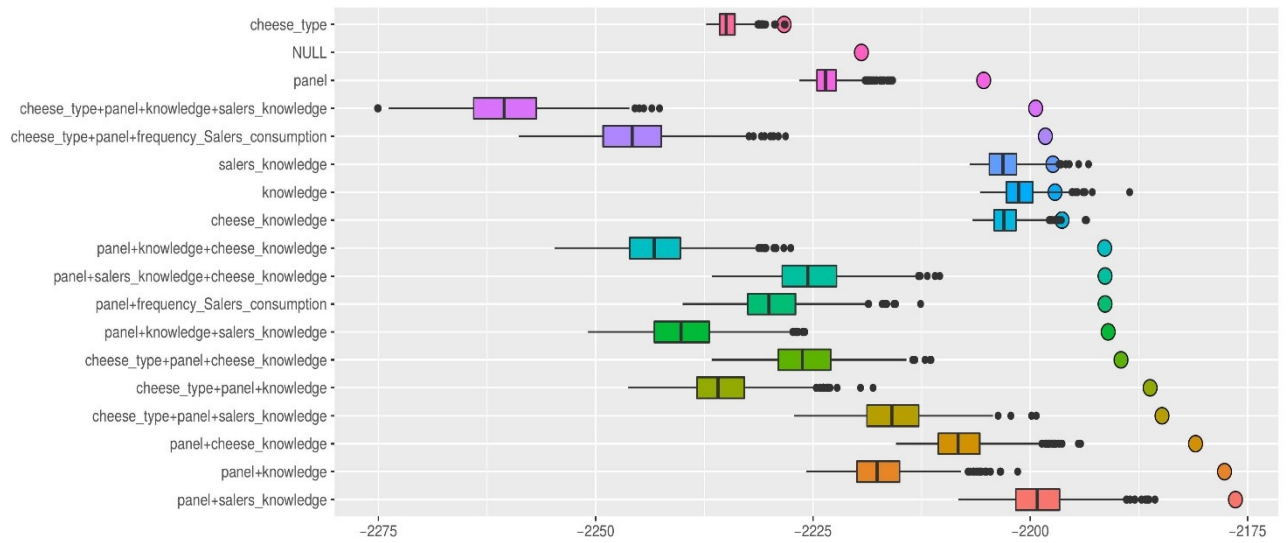
531 Figure 4: Plot from PCA performed on a) cheese categories and b) types of panel (Dim 1-2)

532



533

534 Figure 5: Scores on (a) cheese knowledge and (b) Salers knowledge for each panel



535

536 Figure 6: Plot graphing the BIC criterion according to the different PLN models analyzed

537

538 **Sources of funding**

539 This work was funded by FEADER and the Auvergne- Rhône-Alpes regional council under
540 the rural development program for the project entitled “Innovation Fromagère pour Tradition
541 Salers”.

542 **CRedit authorship contribution statement**

543 **P-M Grollemund:** Formal analysis, Writing – Original Draft, Writing – Review & Editing
544 **C. Bord:** Conceptualization, Methodology, Writing – Original Draft, Writing – Review &
545 Editing. **L. Lenoir and J. Benoit:** Methodology. **C. Chassard:** Supervision.

546 **Declaration of Competing Interest**

547 The authors declare that they have no known competing financial interests or personal
548 relationships that could have appeared to influence the work reported in this paper.

549 **Acknowledgements**

550 The authors thank that many experts who took part in the study, the nonprofit ‘Tradition
551 Salers’ for supplying the cheese samples, René Lavigne from INRAE-UMRF, and René
552 Magneval (cheese-making experts) for their technical expertise. We also thank the consumers
553 and participants in the sensory panels.

554

555 **References**

556 Abdi, H., Valentin, D., Chollet, S., & Chrea, C. (2007). Analyzing assessors and products in sorting tasks:
557 DISTATIS, theory and applications. *Food Quality and Preference*, 18, 627-640.
558 <https://doi.org/10.1016/j.foodqual.2006.09.003>

- 559 Agabriel, C., Martin, B., Sibra, C., Bonnefoy, J.-C., Montel, M.-C., Didiene, R., & Hulin, S. (2004). Effect of
 560 dairy production systems on the sensory characteristics of Cantal cheeses: A plant-scale study. *Animal*
 561 *Research*, 53(3), 221–234. <https://doi.org/10.1051/animres:2004013>
- 562 Anderson, M. J. (2001). Permutation tests for univariate or multivariate analysis of variance and regression.
 563 *Canadian Journal of Fisheries and Aquatic Sciences*, 58(3), 626–639. <https://doi.org/10.1139/f01-004>
- 564 Anderson, M. J. (2017). Permutational Multivariate Analysis of Variance (PERMANOVA). In *Wiley StatsRef:*
 565 *Statistics Reference Online* (pp. 1–15). John Wiley & Sons, Ltd.
 566 <https://doi.org/10.1002/9781118445112.stat07841>
- 567 Bérard, L., Casabianca, F., Montel, M.-C., Agabriel, C., & Bouche, R. (2016). Salers Protected Designation of
 568 Origin cheese, France. The diversity and paradox of local knowledge in geographical indications.
 569 *Culture & History Digital Journal*, 5(1), e006. <https://doi.org/10.3989/chdj.2016.006>
- 570 Bray, J. R., & Curtis, J. T. (1957). An Ordination of the Upland Forest Communities of Southern Wisconsin.
 571 *Ecological Monographs*, 27(4), 325–349. <https://doi.org/10.2307/1942268>
- 572 Cadoret, M., Lê, S., & Pagès, J. (2009). A Factorial Approach for Sorting Task data (FAST). *Food Quality and*
 573 *Preference*, 20(6), 410–417. <https://doi.org/10.1016/j.foodqual.2009.02.010>
- 574 Callon, C., Berdagué, J.-L., Dufour, E., & Montel, M.-C. (2005). The effect of raw milk microbial flora on the
 575 sensory characteristics of salers-type cheeses. *Journal of Dairy Science*, 88(11), 3840–3850.
 576 <https://doi.org/10.1051/lait:198715>
- 577 Chi, M. T. H., Feltovich, P. J., & Glaser, R. (1981). Categorization and Representation of Physics Problems by
 578 Experts and Novices*. *Cognitive Science*, 5(2), 121–152. https://doi.org/10.1207/s15516709cog0502_2
- 579 Chiquet, J., Mariadassou, M., & Robin, S. (2021). The Poisson-Lognormal Model as a Versatile Framework for
 580 the Joint Analysis of Species Abundances. *Frontiers in Ecology and Evolution*, 9.
 581 <https://www.frontiersin.org/article/10.3389/fevo.2021.588292>
- 582 Chollet, S., & Valentin, D. (2000). Le degré d'expertise a-t-il une influence sur la perception olfactive ?
 583 Quelques éléments de réponse dans le domaine du vin. *L'Année psychologique*, 100(1), 11–36.
 584 <https://doi.org/10.3406/psy.2000.28625>
- 585 Cornu, A., Rabiau, N., Kondjoyan, N., Verdier-Metz, I., Pradel, P., Tournayre, P., Berdagué, J. L., & Martin, B.
 586 (2009). Odour-active compound profiles in Cantal-type cheese: Effect of cow diet, milk pasteurization
 587 and cheese ripening. *International Dairy Journal*, 19(10), 588–594.
 588 <https://doi.org/10.1016/j.idairyj.2009.04.008>

- 589 Deegan, K. C., Koivisto, L., Näkkilä, J., Hyvönen, L., & Tuorila, H. (2010). Application of a sorting procedure
 590 to greenhouse-grown cucumbers and tomatoes. *LWT - Food Science and Technology*, 43(3), 393–400.
 591 <https://doi.org/10.1016/j.lwt.2009.08.014>
- 592 Faye, P., Brémaud, D., Durand Daubin, M., Courcoux, P., Giboreau, A., & Nicod, H. (2004). Perceptive free
 593 sorting and verbalization tasks with naive subjects: An alternative to descriptive mappings. *Food*
 594 *Quality and Preference*, 15(7), 781–791. <https://doi.org/10.1016/j.foodqual.2004.04.009>
- 595 Faye, P., Brémaud, D., Teillet, E., Courcoux, P., Giboreau, A., & Nicod, H. (2006). An alternative to external
 596 preference mapping based on consumer perceptive mapping. *Food Quality and Preference*, 17(7), 604–
 597 614. <https://doi.org/10.1016/j.foodqual.2006.05.006>
- 598 Gawel, R. (1997). The Use of Language by Trained and Untrained Experienced Wine Tasters. *Journal of*
 599 *Sensory Studies*, 12(4), 267–284. <https://doi.org/10.1111/j.1745-459X.1997.tb00067.x>
- 600 Giboreau, A., Navarro, S., Faye, P., & Dumortier, J. (2001). Sensory evaluation of automotive fabrics: The
 601 contribution of categorization tasks and non verbal information to set-up a descriptive method of tactile
 602 properties. *Food Quality and Preference*, 12(5), 311–322. [https://doi.org/10.1016/S0950-](https://doi.org/10.1016/S0950-3293(01)00016-7)
 603 [3293\(01\)00016-7](https://doi.org/10.1016/S0950-3293(01)00016-7)
- 604 Holliins, M., Faldowski, R., Rao, S., & Young, F. (1993). Perceptual dimensions of tactile surface texture: A
 605 multidimensional scaling analysis. *Perception & Psychophysics*, 54(6), 697–705.
 606 <https://doi.org/10.3758/BF03211795>
- 607 Honoré-Chedozeau, C., Desmas, M., Ballester, J., Parr, W. V., & Chollet, S. (2019). Representation of wine and
 608 beer: Influence of expertise. *Current Opinion in Food Science*, 27, 104–114.
 609 <https://doi.org/10.1016/j.cofs.2019.07.002>
- 610 ISO 13299:2016. *Analyse sensorielle—Méthodologie—Directives générales pour l'établissement d'un profil*
 611 *sensoriel*. (2016). AFNOR. <https://www.iso.org/obp/ui/#iso:std:iso:13299:ed-2:v1:fr>
- 612 Lawless, H. T., & Glatter, Sandy. (1990). Consistency of Multidimensional Scaling Models Derived from Odor
 613 Sorting. *Journal of Sensory Studies*, 5(4), 217–230. [https://doi.org/10.1111/j.1745-](https://doi.org/10.1111/j.1745-459X.1990.tb00492.x)
 614 [459X.1990.tb00492.x](https://doi.org/10.1111/j.1745-459X.1990.tb00492.x)
- 615 Lawless, H. T., Sheng, N., & Knoops, S. S. C. P. (1995). Multidimensional scaling of sorting data applied to
 616 cheese perception. *Food Quality and Preference*, 6(2), 91–98. [https://doi.org/10.1016/0950-](https://doi.org/10.1016/0950-3293(95)98553-U)
 617 [3293\(95\)98553-U](https://doi.org/10.1016/0950-3293(95)98553-U)

- 618lba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*,
619 13(4), 411–454. <http://www.jstor.org/stable/2489367>Journal of Consumer Research
- 620Lelièvre, M., Chollet, S., Abdi, H., & Valentin, D. (2008). What is the validity of the sorting task for describing
621 beers? A study using trained and untrained assessors. *Food Quality and Preference*, 19(8), 697–703.
622 <https://doi.org/10.1016/j.foodqual.2008.05.001>
- 623Lelièvre, M., Chollet, S., Abdi, H., & Valentin, D. (2009). Beer-Trained and Untrained Assessors Rely More on
624 Vision than on Taste When They Categorize Beers. *Chemosensory Perception*, 2(3), 143–153.
625 <https://doi.org/10.1007/s12078-009-9050-8>
- 626Meilgaard, M. C., Civille, G. V., & Carr, B. T. (2015). *Sensory Evaluation Techniques* (5th ed.). CRC Press.
- 627Merlo, T. C., Saldaña, E., Patinho, I., Selani, M. M., & Contreras-Castillo, C. J. (2022). 10 - Free sorting task
628 method to optimize the development of smoked bacon: A case study. In J. M. Lorenzo, M. Pateiro, E.
629 Saldaña, & P. E. S. Munekata (Eds.), *Sensory Analysis for the Development of Meat Products* (pp. 173–
630 179). Woodhead Publishing. <https://doi.org/10.1016/B978-0-12-822832-6.00010-2>
- 631Moussaoui, K. A., & Varela, P. (2010). Exploring consumer product profiling techniques and their linkage to a
632 quantitative descriptive analysis. *Food Quality and Preference*, 21(8), 1088–1099.
633 <https://doi.org/10.1016/j.foodqual.2010.09.005>
- 634Nacef, M., Lelièvre-Desmas, M., Symoneaux, R., Jombart, L., Flahaut, C., & Chollet, S. (2019). Consumers’
635 expectation and liking for cheese: Can familiarity effects resulting from regional differences be
636 highlighted within a country? *Food Quality and Preference*, 72, 188–197.
637 <https://doi.org/10.1016/j.foodqual.2018.10.004>
- 638Parr, W. V., Valentin, D., Green, J. A., & Dacremont, C. (2010). Evaluation of French and New Zealand
639 Sauvignon wines by experienced French wine assessors. *Food Quality and Preference*, 21(1), 56–64.
640 <https://doi.org/10.1016/j.foodqual.2009.08.002>
- 641Popper, R., & Heymann, H. (1996). Analyzing Differences Among Products and Panelists by Multidimensional
642 Scaling. In *Data Handling in Science and Technology* (Vol. 16, pp. 159–184). Elsevier.
643 [https://doi.org/10.1016/S0922-3487\(96\)80030-X](https://doi.org/10.1016/S0922-3487(96)80030-X)
- 644Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, 6(2), 461–464. JSTOR.
645 <http://www.jstor.org/stable/2958889>

- 646Soufflet, I., Calonnier, M., & Dacremont, C. (2004). A comparison between industrial experts' and novices'
647 haptic perceptual organization: A tool to identify descriptors of the handle of fabrics. *Food Quality and*
648 *Preference*, 15(7), 689–699. <https://doi.org/10.1016/j.foodqual.2004.03.005>
- 649Varela, P., & Ares, G. (2012). Sensory profiling, the blurred line between sensory and consumer science. A
650 review of novel methods for product characterization. *Food Research International*, 48(2), 893–908.
651 <https://doi.org/10.1016/j.foodres.2012.06.037>
- 652