

1 **Identifying temporal drivers of liking and satiation based on temporal sensory**
2 **descriptions and consumer ratings**

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10 **Abstract**

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3 11 Capturing temporal sensory changes has been the focus in recent research to better
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6 12 understand how consumers perceive food products. This information can be linked to
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8 13 consumer expectations (e.g., liking, satiety) to study the sensory drivers throughout
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10 14 the eating experience, namely *temporal drivers*. This study explores the use of penalty-
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13 15 lift analyses for each time point in the temporal sensory description to identify the
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15 16 temporal drivers of liking/ satiety for different groups of consumers with different
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18 17 patterns in their expectations of satiety.

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21 18 Eight yoghurt samples formulated based on an experimental design, with identical
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24 19 composition, varying in textural properties, were used in the study. Temporal Check-
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26 20 All-That-Apply (TCATA) was used to describe dynamic sensory profiles. Consumers
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29 21 (n=101) tasted each yoghurt and rated their liking and expected satiety.

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32 22 Cluster analysis of variables around latent variables (CLV) method was applied to
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35 23 cluster consumers based on their expectations of satiety, detecting two relevant
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37 24 clusters.

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40 25 Penalty-lift analysis was used for each time point. Also, the false discovery rate (FDR)
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43 26 was applied to correct p-values for multiple tests responding to sequential time points.

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45 27 Differences were found related to how particle size attributes and flavour intensities
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48 28 drove liking for each cluster at different time points. For cluster 1, while Gritty was
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50 29 positive driver from the middle to the end, Sandy was negative driver in the middle;
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53 30 and Vanilla was positive driver of liking throughout the mastication. For cluster 2, only
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55 31 Sweet was pointed as positive driver at the beginning, and Dry as negative driver in
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58 32 some time points at the middle of the mastication.

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33 With regards to expected satiety, main difference was that Gritty (or Sandy) was
34 considered as positive (or negative) driver for cluster 1, but not for cluster 2; significant
35 over the entire time period.

36 These findings demonstrate that the temporal driver approach appears as a suitable
37 method to unveil the drivers of liking/satiety during the eating process in groups of
38 consumers with different eating behaviours and preferences.

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40 **Keywords:** *liking; satiety; penalty-lift analysis; temporal driver; yoghurt*

41 **1. Introduction**

42 *Dynamic sensory perception in food product development*

43 In sensory and consumer science, various techniques can be used to gain a better
44 understanding of what sensory characteristics of food products are responsible for the
45 perceived quality of the products, including Preference mapping (McEwan, 1996),
46 Just-about-right (Plaehn & Horne, 2008; Popper, 2014; Xiong & Meullenet, 2006),
47 Ideal Profile method (van Trijp, Punter, Mickartz, & Kruithof, 2007), Check-all-that-
48 apply (Adams, Williams, Lancaster, & Foley, 2007; Ares, Varela, Rado, & Giménez,
49 2011; Dooley, Lee, & Meullenet, 2010; Plaehn, 2012), and other techniques. In
50 general, these techniques have focused on static sensory perceptions (Di Monaco, Su,
51 Masi, & Cavella, 2014) and related them to consumer expectations (e.g., liking,
52 satiation, satiety) to identify drivers of consumer expectations. Sensory perception,
53 however, changes from the first bite to the swallowing point in response to different
54 stages of the mastication (Morell, Fiszman, Varela, & Hernando, 2014). Therefore, it
55 becomes necessary to describe sensory attributes as dynamic perceptions. Several
56 temporal descriptive methods have been proposed to investigate temporality in
57 sensory perceptions, including Time Intensity (TI) (Lee & Pangborn, 1986), Dual
58 Attribute Time Intensity (DATI) (Duizer, Bloom, & Findlay, 1997), Multi Attribute Time
59 Intensity (MATI) (Kuesten, Bi, & Feng, 2013), Temporal Dominance of Sensations
60 (TDS) (Pineau, Cordelle, & Schlich, 2003), and Temporal Check-all-that-apply
61 (TCATA) (Castura, Antúnez, Giménez, & Ares, 2016). In general, tracking the intensity
62 of more than one attribute continuously over time is very complex (Schlich, 2017).
63 Thus, the focus here will be on the temporal methods [that record presence / absence](#)
64 [of many attributes simultaneously over time, and the](#) selection of attributes according
65 to dominant sensations (in case of TDS), or applicable sensations (in case of TCATA).

66 *Methods to investigate temporal drivers of liking (TDL)*

67 In general, there are two ways to record liking over time: *dynamic liking*, where the
68 subject gives liking score after each intake, and *temporal liking*, where the subject
69 continuously rates his liking score within and between intakes (Thomas et al., 2017).
70 Depending on the products, the first or the last sensation perceived by the subject has
71 more impact on the “hedonic image” of the product (Thomas, Visalli, Cordelle, &
72 Schlich, 2015). Some research indicates that the global agreement between classical
73 and temporal liking is quite good (Sudre, Pineau, Loret, & Martin, 2012; Thomas et al.,
74 2015), and consumer hedonic perception is not very different between bites (Antúñez,
75 Giménez, Alcaire, Vidal, & Ares, 2017). For that reason, we will focus on overall liking
76 in this paper, as related to temporal description.

77 Several approaches have been tested to determine which sensations are dominant
78 when liking of a product increases or decreases (Silva et al., 2018). Thomas et al.
79 (2015) have introduced the concept of *Liking While Dominant (LWD)*, calculated as the
80 average of the n individual temporal liking scores while the attribute was dominant, to
81 identify Temporal Drivers of Liking (TDL). If the LWD is significantly larger than the
82 mean liking, the attribute can be considered as a positive TDL; if significantly lower,
83 the attribute is a negative TDL. In the follow-up study, these authors have developed
84 the method called Alternated Temporal Drivers of Liking (A-TDL) where temporal liking
85 is alternated with TDS in the same session (Thomas, van der Stelt, Prokop, Lawlor, &
86 Schlich, 2016), and the method called Simultaneous Temporal Drivers of Liking (S-
87 TDL) in which consumers perform TDS and temporal liking simultaneously using the
88 same data acquisition screen (Thomas et al., 2017). This approach has been shown
89 as effective methodology for characterizing TDL; however, some points need to be

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90 considered carefully. First, analyzing the LWD data one assumes that the length of
91 time an attribute is dominant affects liking (Carr & Lesniasuskas, 2016). A potential
92 drawback is that LWD calculation only focuses on the dominant attribute, while non-
93 significant variables (in particular in case of small sample sizes) might be related to
94 liking as well (Meyners, 2016). Second, this approach enables identification of drivers
95 of liking for a certain product, not for all products. Lastly, it loses the temporality of
96 drivers since temporal drivers of each product are identified by comparing LWD values
97 with the mean liking over the quotations weighted by their durations.

98 In another approach, TDS data are split into four **equal** time periods, and considered
99 as Check-all-that-apply (CATA) per period (Meyners & Castura, 2014). In order to
100 determine the impact of the attributes on the hedonic response, a penalty-lift analysis
101 (Williams, Carr, & Popper, 2011) is performed on the CATA-coded TDS data and the
102 averages of the temporal liking scores (Meyners, 2016). This approach deals with the
103 identification of positive, negative, and non-drivers of liking for all products, but the
104 temporality of sensory drivers is still not considered. In the approach, the splitting is
105 done by dividing time durations into four periods of time (Q1 to Q4) as proposed by
106 previous research (Ares et al., 2017; Dinnella, Masi, Naes, & Monteleone, 2013);
107 however, the data-driven splitting (Nguyen, Næs, & Varela, 2018; Nguyen, Wahlgren,
108 Almlí, & Varela, 2017) should be investigated if it could provide further information.

109 *Individual differences*

110 In oral processing, the physiological aim is to produce a suitable bolus for
111 swallowing; however, subjects have different strategies to obtain a swallowable bolus
112 (Mishellany, Woda, Labas, & Peyron, 2006). More specifically, subjects have preferred
113 ways to manipulate and manage food in mouth and this behavior determines the food

114 texture they prefer; that is, the key drivers of liking and other expectations (Brown &
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2 115 Braxton, 2000; Jeltema, Beckley, & Vahalik, 2016). Recently, Varela, Mosca, Nguyen,
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4 116 McEwan, and Berget (2021) highlight that different groups of consumers are driven by
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7 117 distinct textural attributes when assessing liking and satiety, differently influencing their
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10 118 intake. Furthermore, Nguyen and colleagues speculated that dynamic sensory
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12 119 perception was key in defining satiety expectations (Nguyen et al., 2017) and that
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14 120 consumers with different eating styles would have different reactions to textural
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17 121 changes (Nguyen, Næs, Almøy, & Varela, 2020). Therefore, it is important to see how
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19 122 individual differences influence the relations between consumer ratings and dynamic
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22 123 sensory perceptions.

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25 124 We propose a new way of analyzing together temporal sensory data and consumer
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27 125 ratings. This method consists of splitting temporal data into CATA-coded data for each
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30 126 time point, then applying penalty-lift analysis sequentially to each split data in order to
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32 127 identify sensory drivers, and finally combining these drivers to draw temporal driver
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35 128 curves. Both temporal drivers of liking and expected satiety are considered as some
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37 129 research highlights that the extension beyond liking may allow us to deepen our
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40 130 understanding of the consumption experience (Thomas, van der Stelt, Schlich, &
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42 131 Lawlor, 2018). The paper will focus on methodological issues such as interpretability
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45 132 and added value of the results.

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134 **2. Materials and methods**

135 *2.1. Yoghurt data collection*

136 The yoghurt data set consists of sensory description and consumer data that is
137 described in more details in previous research (Nguyen et al., 2020; Nguyen et al.,
138 2018). In brief, eight yoghurt samples were prepared from an experimental design
139 based on the same ingredients, only modifying the product texture by using different
140 processing strategies. A trained panel was used to evaluate yoghurt samples
141 according to the TCATA method (Castura et al., 2016) with the pre-defined list of
142 sensory attributes. In a consumer test, 101 consumers were asked to taste each
143 sample and rate their liking on a Labelled Affective Magnitude (LAM) scale, 0 to 100
144 as in Schutz and Cardello (2001), and expected satiety on a 6-point scale in which 1 =
145 “hungry again at once”, 2 = “full for up to one hour”, 3 = “full for up to two hours”, 4 =
146 “full for up to three hours”, 5 = “full for up to four hours”, 6 = “full for five hours or longer”.
147 In principle, satiety is used to describe the post-ingestive processes that occur after a
148 meal and inhibit further eating, and includes the suppression of hunger and a feeling
149 of fullness during the inter-meal period (Blundell et al., 2010).

150 All the sensory evaluations were conducted in standardized individual booths
151 according to ISO 8589:2007 . Samples were coded with 3-digit random numbers and
152 served in plastic containers, in a sequential monadic manner, following a balanced
153 presentation order design.

154 *2.2. Data analysis*

155 *2.2.1. Cluster analysis using the Clustering around Latent Variables (CLV) approach*

156 The underlying principle of the CLV method is as follows: find K groups of variables
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2 157 G_1, G_2, \dots, G_k and K latent components T_1, T_2, \dots, T_k associated respectively with the K
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5 158 groups such that the variables in each group are as much correlated as possible to the
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7 159 corresponding latent variable (Vigneau, Qannari, Punter, & Knoops, 2001). Detailed
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10 160 description of the approach is beyond the scope of this paper, but the interested reader
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12 161 is referred to Vigneau, Chen, and Qannari (2015); Vigneau, Endrizzi, and Qannari
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14 162 (2011); Vigneau and Qannari (2002); Vigneau and Qannari (2003); Vigneau, Qannari,
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17 163 Navez, and Cottet (2016).

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20 164 When applied in the present paper, the clustering was aimed at identifying segments
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23 165 of consumers having highly correlated directions of expected satiety. In an attempt to
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25 166 set aside the “noise” consumers, an improvement of CLV clustering using the $K + 1$
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28 167 strategy was applied (Dave, 1991). (Vigneau, Qannari, Punter, & Knoops, 2001). In
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30 168 particular, the “noise cluster” contains hidden consumers who are expected to have
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33 169 the [same or low correlation](#), ρ , with all the observed consumers. The parameter ρ is
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35 170 selected according to the estimated communality (i.e. internal homogeneity criterion)
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38 171 H_k , the estimate of the effect size (i.e. discrimination ability) d_k (Vigneau et al., 2016).
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41 172 The unbalanced nested ANOVA was applied on expected satiety, considering
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43 173 product (fixed effect), cluster (fixed effect), consumer nested within cluster (random
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46 174 effect) and interaction of product and cluster (fixed effect) as sources of variation. It is
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48 175 noted that the model would be unbalanced as the number of consumers in clusters
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51 176 could be different.

54 177 *2.2.2. Multiple Factor Analysis (MFA) on aggregated data*

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58 178 The temporal data was split into smaller time intervals for interpretation (T0-T40:
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60 179 beginning; T41-T80: middle; T81-T100: end), where the number and duration of time
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180 intervals were chosen according to TCATA curves (Dinnella et al., 2013; Nguyen et al.,
181 2018; Nguyen et al., 2017). A perceptual map was obtained by applying MFA on
182 sensory attributes for each time interval. The scores were calculated as the average of
183 the scores given to an attribute during an evaluation weighted by their duration (Labbe,
184 Schlich, Pineau, Gilbert, & Martin, 2009) rather than the dominant (or applicable)
185 durations of the sensory attributes (Thomas et al., 2015). In addition, liking (and
186 expected satiety) for each cluster were considered as supplementary variables and
187 projected on the perceptual map to identify temporal drivers of liking (and expected
188 satiety).

189 *2.2.3. Penalty-lift analysis with p-values corrected by the false discovery rate (FDR)*

190 In penalty-lift analysis, liking (or expected satiety) ratings were averaged across all
191 observations (consumers and products) in which the attribute was used to characterize
192 the product, and across those observations for which it was not (Meyners, Castura, &
193 Carr, 2013).

194 Calculating the differences between those averages, one could estimate the change
195 in liking (or expected satiety) due to this attribute being checked versus not checked in
196 the CATA questions. In some cases, the sample sizes of two average values (one is
197 average when an attribute is selected, other when this attribute is not selected) was
198 not reasonably large. Therefore, the significance of difference was checked using a
199 randomization test (Edgington & Onghena, 2007; Meyners et al., 2013; Meyners &
200 Pineau, 2010) instead of t-test assuming equal variance.

201 For certain sensory attributes, randomization tests were applied in a large number
202 of times (for example, 100 times in case of TDS or TCATA data with standardized
203 evaluation time) to identify if the attribute affected the changes in liking (or expected

204 satiety) significantly over time, resulting in a multiple testing. For this multiple testing,
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2 205 probability of a false positive in this scenario was now inflated and clearly required
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4 206 adjusting the original single test significance level of 0.05 (Balding, 2006).
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8 207 Although a number of different multiple testing correction methods exist, the false
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10 208 discovery rate (FDR), proposed by Schweder and Spjøtvoll (1982) and Benjamini and
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12 Hochberg (1995), has proven to be reliable as statistical criteria to determine the
13 209 significance in high-dimensional testing (Strimmer, 2008). Rather than controlling the
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15 210 false positive rate, the FDR controlled the false discovery rate. Particularly, FDR was
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17 211 the expected proportion of false positives among all positives which rejected the null
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19 212 hypothesis and not among all the tests undertaken as shown in Eq. (1)
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$$False\ Discovery\ Rate\ (FDR) = Expected\left(\frac{False\ Positive}{False\ Positive + True\ Positive}\right) \quad (1)$$

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33 214 In the FDR method, p-values were ranked in an ascending array and multiplied by
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35 215 m/k where k is the position of a p-value in the sorted vector and m is the number of
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37 independent tests (Jafari & Ansari-Pour, 2019). The interested reader is referred to
38 216 Benjamini and Yekutieli (2001); Jafari and Ansari-Pour (2019); Strimmer (2008); Wright
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40 217 (1992) for detailed description of FDR and other correction approaches.
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46 219 All analyses were carried out using R version 4.0.2 (R Core Team, 2020) with add-
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48 on packages ClustVarLV (Vigneau et al., 2015), lmerTest (Kuznetsova, Brockhoff, &
49 220 Christensen, 2017), FactoMineR (Lê, Josse, & Husson, 2008), and EnvStats (Millard,
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51 221 2013).
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224 3. Results

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3 225 In this paper the segmentation analysis was based on consumer groups with
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5 226 differentiated satiety expectation patterns, and liking differences were investigated
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8 227 considering those consumer clusters. The idea behind was better understanding how
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11 228 liking and satiety expectations play a role, together with dynamic perception, as they
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13 229 may in turn influence food intake. In their previous work, Varela et al. (2021) highlighted
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15 230 the importance of considering individual differences, and how liking and satiety
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18 231 expectations can have a different role; they observed consumer groups reacted
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20 232 differently to the changes in yoghurt texture in terms of amount eaten and liking
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23 233 responses, suggesting that different patterns in intake and liking may be related to
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25 234 different eating styles.

27 28 29 235 *3.1. Clustering of consumers according to expected satiety*

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32 236 The CLV clustering using the $K + 1$ strategy started with the determination of
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34 237 number of clusters. Considering the aggregation criterion Δ , it was shown that the
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37 238 aggregation criterion fell when passing from a solution with three clusters to those of
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40 239 two clusters. This suggested that “unnatural” clusters were being merged, and
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42 240 therefore two clusters ($K = 2$) were retained for the subsequent analyses. The noise
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44 241 cluster was determined according to the threshold value ρ . In principle, it was selected
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47 242 to compromise between the number of discarded consumers and the expectation
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50 243 regarding the characteristics of the noise cluster. The threshold value ρ was selected
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52 244 based on the communality index (H_k) and effect size (d_k); particularly, the values of ρ
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54 245 leading to the smallest internal homogeneity (H_k) and the smallest discrimination ability
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57 246 (d_k) associated with the “noise cluster” could be singled out. Based on this, the ρ of
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59 247 0.43 was chosen (data not shown). With the determination of number of clusters ($K =$

2) and threshold value ($\rho = 0.43$), the final clusters were obtained, including cluster 1 (n = 36), cluster 2 (n = 58), and noise cluster (n = 7). Then, clusters 1 and 2 are used in subsequent analysis.

3.2. Liking and expected satiety patterns in each cluster

As stated above, eight products were prepared from an experimental design (viscosity, particle size, and flavour intensity variables). Due to the different number of consumers in each cluster, an unbalanced nested ANOVA was used to investigate the *product* and *cluster* effects. The ANOVA results revealed that both effects *product* and *cluster* as well as their interaction were significant for expected satiety with p-values of <0.001, 0.009, and <0.001, respectively. Particularly, the products TkFkL, TkFrL, TkFkH, TkFrH were rated higher in expected satiety than the ones TnFkL, TnFrL, TnFkH, TnFrH. However, the significance of interaction (product*cluster) indicates that both clusters have differentiated patterns with regards of assessing expected satiety. For each cluster, the differences between products in liking (or expected satiety) were also considered.

Ratings of expected satiety in cluster 1 were higher than those in cluster 2 for all products (Fig. 1). In both clusters, the differences in expected satiety were strongly influenced by the consistency of the matrix (thick/thin). In particular, the thick products (TkFkL, TkFrL, TkFkH, TkFrH) were rated higher in expected satiety than the thin ones (TnFkL, TnFrL, TnFkH, TnFrH). However, the main difference among clusters was on how they rated the thick samples; expected satiety of consumers in cluster 2 was related to yoghurt thickness: all thick samples, regardless of with added flakes (Fk) or flour (Fr) were rated higher in expected satiety, and all the thin samples were significantly lower. Expected satiety of consumers in cluster 1 however, was also

272 related to the particle size. Thick samples were rated higher in cluster 1, but yoghurts
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2 273 with flakes (Fk) were rated significantly higher as compared to the flour ones (TkFkL >
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4 274 TkFrL, TkFkH > TkFrH). In particular, the expected satiety of thick-flakes samples
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7 275 (TkFkL, TkFkH) was found as significantly higher than the same samples for cluster 2.
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10 276 As can be seen in Fig. 1, ratings of expected satiety of the products TkFrL and
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13 277 TnFkH were not significantly different in cluster 1. That indicates the influence of the
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15 278 interaction between two factors: viscosity (thick vs. thin), and particle size added (flour
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18 279 vs. flakes) on ratings of expected satiety. This result is in agreement with the finding in
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20 280 our previous study (with the same data) in which, by applying PCA on expected satiety
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23 281 coupled with sensory description, Nguyen et al. (2020) highlighted that two main
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25 282 components, driven by particle-size and viscosity, explained the separation of these
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28 283 same products. Further explanation should be provided in the subsequent part when
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30 284 temporal drivers of expected satiety considered.
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33 285 Hedonic ratings (liking) of the different products are depicted in Fig. 2. The results
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36 286 were generally in line with the results of expected satiety, but with some differences
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39 287 (the products being high in liking are high in expected satiety, and conversely). More
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41 288 specifically, there were two groups of products: thick products (TkFkL, TkFrL, TkFkH,
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43 289 TkFrH) and thin products (TnFkL, TnFrL, TnFkH, TnFrH), where thicker ones were
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46 290 generally better liked in both clusters. However, one of the thin samples was
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48 291 particularly well liked in cluster 1 (TnFkH), which was not the case in cluster 2. Liking
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51 292 and expected satiety followed similar patterns in cluster 2, but this was not so clear for
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53 293 cluster 1.
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56 294 3.3. Temporal drivers of liking/ expected satiety for each cluster

57 295 3.3.1. Drivers based on time intervals by applying MFA on aggregated data

296 As reminder, time duration was split into three time intervals: beginning (b), middle
297 (m), and end (e). Then, in the rest of this section, sensory perceptions should be
298 considered as perceptions at different time intervals with the prefix *b.*, *m.*, *e.* responding
299 to *beginning*, *middle*, and *end* of the mastication.

300 The perceptual map (Fig. 3), multiple factor analysis based on the temporal sensory
301 attributes, at different time intervals (beginning, middle, end), points the cluster 1 and
302 2 vectors for liking and expected satiety are all pointing in the same direction.

303 Thickness was found to be the most important driver of liking (and expected satiety)
304 for both clusters. The perception of yoghurt thickness during the eating process
305 increased the liking and expected satiety as compared to being not perceived – i.e.
306 thick perceptions at the beginning (*b.Thick*), middle (*m.Thick*) and end (*e.Thick*); added
307 to this, the perception of thinness reduced both liking and expected satiety – i.e.
308 (*b.Thin*, *m.Thin*, *e.Thin*). These results supported the previous observations,
309 highlighting that thick products were rated high in both liking and expected satiety as
310 compared to thin products. However, there were also some differences in temporal
311 drivers for cluster 1 and 2.

312 For cluster 1, in addition to thickness perception, particle-size (gritty vs. sandy) and
313 flavour (sweet, vanilla), attributes mainly correlated to the first component of the MFA,
314 also contributed to the changes in liking (L-S1) and expected satiety (S-S1). Fig. 3
315 shows that while gritty perceptions during the mastication (*b.Gritty*, *m.Gritty*, *e.Gritty*)
316 were positively related to L-S1 and S-S1 (i.e. increased liking and expected satiety of
317 cluster 1), dry at the beginning (*b.Dry*) and sandy at the beginning (*b.Sandy*) as being
318 negatively related. The flavour perceptions (*b.Vanilla*, *m.Vanilla*, *e.Vanilla*) led to an

319 increase in liking (*L-S1*), but did not have very clear influence in expected satiety (*S-*
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2 320 *S1*).

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5 321 For cluster 2, liking (*L-S2*) and expected satiety (*S-S2*) were more related to the
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8 322 second dimension, mainly driven by texture (thick vs. thin), and perpendicular (not
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10 323 correlated) to the first dimension (gritty/vanilla vs sandy/bitter).

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14 324 Even if the MFA plot ([Fig. 3](#)) highlights some differences between clusters, the
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16 325 observation of the multidimensional space shows the vectors for both clusters pointing
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19 326 to the same quadrant, with the consequent difficulty of interpretation.

20 21 22 327 *3.3.2. Drivers of liking and expected satiety based on the time continuum*

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26 328 For a better understanding the temporal drivers, we propose an analysis of all the
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28 329 time points.

29 30 31 32 330 *Temporal drivers of expected satiety*

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35 331 Applying sequential penalty-lift analysis, [Fig. 4](#) highlights the evolution of sensory
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38 332 drivers of expected satiety over time. The graphical display suggests *Thick* as a
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40 333 positive driver of expected satiety, while *Thin* results in lower expected satiety for both
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43 334 clusters, consistent with the previous findings based on time intervals.

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46 335 The main differences between clusters were regarding the influence of particle-size
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48
49 336 (*Gritty* vs. *Sandy*). Cluster 1 associated gritty texture with higher satiety and sandy
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51 337 texture with lower satiety, but this association was not found in cluster 2. It is worth
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53 338 noting that they were significant over all consumption time (i.e. from the beginning to
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56 339 end of the eating process). In cluster 2, *Dry* was found to be a negative driver during
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58 340 T55-T70. To a certain extent, these results here are more straightforward to interpret

341 as compared with the display in which sensory perceptions were considered on
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2 342 different time intervals (Fig. 3). These results, based on time continuum, demonstrate
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5 343 that consumers in cluster 1 considered both thickness and particle-size variables when
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7 344 they rated expected satiety, whereas consumers in cluster 2 focused on thickness only
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10 345 when they rated their expected satiety. Moreover, similar to the drivers based on time
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12 346 intervals, flavour perceptions did not play a significant role in any of the clusters.
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15 347 *Temporal drivers of liking*

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19 348 The sequential penalty-lift analysis applied to the liking data (Fig. 5) shows the
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21 349 temporal drivers of liking for cluster 1 and 2. Thickness was the major driver of liking
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24 350 for the two clusters; particularly, *Thick* increased whereas *Thin* reduced hedonic
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26 351 ratings. Similar to the expected satiety results, the influence of thickness (*Thick* vs.
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28 352 *Thin*) on liking occurred throughout all the eating process.
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32 353 For cluster 1, *Gritty* and *Sandy* led to high and low hedonic ratings, respectively.
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34 354 *Gritty* was a strong driver of liking from the middle to end of the evaluation (T20-T100),
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37 355 while grittiness at the beginning was not significantly associated with a higher liking
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39 356 (T0-T20). Meanwhile, *Sandy* showed up as negative driver at the middle only (T20-
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42 357 T60), decreasing the liking if present during this time. At the end of the evaluation,
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44 358 *Sandy* appeared as a negative driver in some time points.
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48 359 Regarding flavour attributes, the temporal drivers of liking shown in Fig. 5 indicated
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50 360 that liking was associated with sweet perceptions (*Sweet*, *Vanilla*). As can be seen,
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53 361 the effect of *Vanilla* on liking was strongest at the beginning, and gradually declined
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55 362 until T10. After that, *Sweet* appeared as the main taste that increased liking (T10-T20).
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57 363 Finally, *Vanilla* appeared again as positive driver of liking until the end of the
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364 consumption. In general, both *Sweet* and *Vanilla* can be considered as positive drivers
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2 365 of liking.
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5 366 For cluster 2, the drivers of liking were quite clear. In addition to *Thick/Thin* attributes
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8 367 as positive/negative drivers over time, it was shown that *Sweet* increased liking only at
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10 368 the beginning (T10-T20) similarly to cluster 1. Unlike cluster 1, in some time points at
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12 369 the middle (T55-T70), *Dry* was a negative driver of liking.
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371 4. Discussion

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3 372 The results of the present paper build on the ideas that among sensory dimensions,
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6 373 texture determines expectations of satiation and satiety further than flavour does
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8 374 (Chambers, 2016; Hogenkamp, Stafleu, Mars, Brunstrom, & de Graaf, 2011), and that
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10 375 textural attributes (consistency, particle size) can differently drive satiety expectations
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13 376 in diverse groups of consumers, as previously suggested by Nguyen et al. (2020).
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15 377 These findings are in agreement with Varela et al. (2021) that found, in a similar case
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18 378 study, that three groups of consumers reacted differently to yoghurt textures in terms
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20 379 of amount eaten, depending on yoghurt thickness and granola particle size. However,
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23 380 the consumer segments in the present study, and in Varela et al. (2021) were built
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25 381 based on different parameters (expected satiety vs amount eaten) so care should be
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28 382 taken in the generalization, and more research with different products and different
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30 383 textures should be performed for better understanding of how texture and temporal
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33 384 perception play a role in food intake.

36 385 4.1. Flavour as a driver of liking and expected satiety

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39 386 Regarding flavour perceptions, generally speaking, people prefer sweet tastes and
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42 387 avoid bitter (Shepherd & Raats, 2010). When considering sensory drivers based on
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44 388 time intervals (Fig. 3), vanilla and acidic at the end (*e. Vanilla*, *e. Acidic*) were the only
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47 389 positive drivers of liking for cluster 1; sweet perceptions at different stages of eating
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49 390 process (b, m, e) did not clearly relate to liking (or expected satiety) for cluster 1 or, to
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52 391 a certain extent, negatively impacted liking and expected satiety for cluster 2. However,
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54 392 considering the temporal curves of the same samples (data not shown), Nguyen et al.
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57 393 (2018) indicated that sweet or vanilla were relevant to describe these yoghurt products.
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59 394 The absence of sweet and vanilla could come from the fact that the MFA perceptual
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395 map is obtained using aggregated citation rates over three pre-defined time intervals,
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2 396 which might dilute some signals in the data (Meyners, 2020). That may be a potential
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4 397 drawback of this approach when data are aggregated by time periods. On the contrary,
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7 398 a potential advantage of using the MFA approach, based on aggregated time intervals,
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9 399 could come from the simplicity and summarization of the data display, which can be
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12 400 easier to communicate, given the fact that all clusters and relevant associated
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14 401 attributes for the target measurements can be shown in one bi-dimensional plot (i.e.
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17 402 liking, satiety and all significant attributes split in the time intervals). Multivariate type
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19 403 of plots, similar to PCA plots, are widespread tools that many within the R&D
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22 404 community are accustomed to see (e.g. product developers, marketing, R&D
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24 405 management), making the display useful for results sharing. Nevertheless, one should
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26 406 have in mind that some information in the conclusions could be lost, as it has been
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29 407 shown here for sweet and vanilla; this compromise can have different implications
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31 408 depending on the level of detail the researcher is looking for.

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35 409 The proposed new approach, based on the whole temporal curve, highlights
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37 410 sweetness as a driver of liking in the beginning of the oral processing for both clusters
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40 411 and vanilla as a relevant driver during almost all consumption for cluster 1. This is more
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42 412 in line to what is expected for these kind of products (sweetness as a positive driver)
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45 413 and could mean that considering the whole curve gives more “granularity” to the
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47 414 results, allowing for a better interpretation. The fact of sweetness being important at
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50 415 the beginning of the consumption can be especially relevant in this category, as
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52 416 yoghurt is typically expected to taste acidic, but a certain level of sweetness is required,
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54 417 and seemed to be most important in the beginning, at least for the yoghurts and
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57 418 consumers in this study. Although unveiling more detailed results, the sequential
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59 419 penalty-lift analysis plots, however, are not that easy to communicate outside of the
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420 sensory and consumer science community, which can be a disadvantage at the time
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2 421 of taking action from the results. One could envision then, a potential combination of
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4 422 both data analyses approaches, with different levels of granularity and different
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7 423 applications in terms of results communication. Future work should perhaps look into
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10 424 easier ways of displaying the sequential penalty-lift results.

13 425 4.2. Individual differences underlying liking and expected satiety

16 426 Individuals use different strategies for the oral breakdown of food so that different
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19 427 groups of individuals can experience identical samples differently and this influence
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21 428 their expectations (Brown & Braxton, 2000). Previous studies have highlighted that
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24 429 both viscosity and solid food particles are modulators of satiety expectations
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26 430 (Hogenkamp & Schiöth, 2013; Hogenkamp et al., 2011; Marcano, Morales, Vélez-Ruiz,
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29 431 & Fiszman, 2015). However, it is not clear how these two physical properties together
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31 432 should impact liking and expected satiety for different groups of consumers. In the
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34 433 present work, the effort focused on unveiling some of the influences for diverging
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36 434 groups of consumers, namely temporal perception as driver of satiety-related
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38 435 expectations, which seems to influence them differently.

42 436 Investigating the influence of viscosity and particle size added on oral processing
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44 437 behavior, Mosca et al. (2019) highlight that while a decrease in yoghurt viscosity did
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47 438 not significantly affect eating rate and *ad libitum* intake, a decrease in granola particle
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49 439 size decreased spoon size, eating rate and *ad libitum* intake without affecting liking. It
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52 440 is important to note that these results were obtained without considering individual
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54 441 differences among consumers. Contrary to the above results, some research
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57 442 highlighted that increases in viscosity decreased intake of semi-solid foods (de Wijk,
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59 443 Zijlstra, Mars, de Graaf, & Prinz, 2008; Zijlstra, de Wijk, Mars, Stafleu, & de Graaf,

2009). Possibly, the influence of texture modifications (viscosity and particle size) was averaged, and differences could have been diluted between segments of consumers leading to diverging results. In our previous research (Nguyen et al., 2020; Varela et al., 2021) we showed there certainly are individual differences underlying those phenomena, and highlighted the need for further research to better understand it; the present work is an initial effort towards that direction.

Research by Jeltema, Beckley, and Vahalik (2015); Jeltema et al. (2016) has shown that individuals can be classified by the way they manipulate food in their mouths (i.e. *Chewer, Cruncher, Smoosher, Sucker* consumers). Based on this idea, and applying PLS path modelling, Nguyen et al. (2020) pointed out that *Chewers* and *Crunchers* seemed to use both viscosity and particle-size perceptions for estimating prospective portion size, while *Smoosher*s used particle-size only. In a recent work, Varela et al. (2021) identified three groups of consumers with different intake patterns in response to textural changes in consistency and particle size, including “small eaters”, “thick sensitive”, “small rejectors”. These authors highlighted that the lower intake was more related to the increased viscosity than to the smaller particles.

Similarly, considering expected satiety or liking in the present paper, particle size attributes (*Gritty vs Sandy*) were found to be important attributes that sorted consumers into 2 clusters. One hypothesis could be that consumers reacted according to their tactile sensitivity, in particular regarding grittiness. More specifically, cluster 1 could be seen as a *high grittiness sensitivity* group where consumers perceive the difference in terms of grittiness, or else they give enhanced importance to it, and differently rate expected satiety and liking between the products based on those perceptions. Cluster 2, however, could be described as *low grittiness sensitivity* group including consumers who either do not perceive the difference in terms of grittiness, or perceive it but do not

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2 469 give importance to this attribute to rate expected satiety and liking between the
3 470 products tested.
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6 471 The results here suggest the important role of tactile sensitivity (grittiness in this
7 case) in determining drivers of consumer liking and satiety-related perceptions. Similar
8 472 results have been also observed in the research by Puleo, Miele, Cavella, Masi, and
9 Di Monaco (2019) in which high-graininess-sensitive consumers liked more the most
10 473 refined samples as compared with moderate- and low-graininess-sensitive consumers.
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19 476 These findings highlight the importance of further understanding texture/tactile
20 sensitivity on preferences, expectations of satiety, and food intake as previously
21 477 reported by Forde and Delahunty (2002) and more recently by Puleo et al. (2019).
22 While the importance of texture in food preferences is well documented, there is a
23 478 limited understanding how physiological individual differences in sensitivity would
24 479 influence texture perception which in turn impact consumer preferences, expectations
25 of satiety and food intake. More research should be performed to investigate these
26 480 relations, and how those are related to dynamic sensory perceptions.
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485 5. Conclusions

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3 486 This paper proposes a novel method to explore temporal drivers of consumer
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6 487 perceptions and expectations, liking and expected satiety, but could potentially be
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8 488 applied to other perceptions or expectations that are influenced by temporal sensory
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11 489 perception. This method relies on converting temporal data into CATA-coded data for
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13 490 each time point, applying penalty-lift analysis sequentially to identify sensory drivers,
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15 491 and combining these drivers into temporal driver curves. As compared to temporal
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18 492 drivers based on time intervals, this method, based on the full time continuum, allowed
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20 493 us to see the evolution of sensory drivers over time while maintaining the temporality
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23 494 of the data, and allowing for a more detailed interpretation. Coupled with clustering of
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25 495 consumers, this approach can provide new insights for better understanding how
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28 496 temporal perception influences consumers choices.

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31 497 Furthermore, in a time where personalization is increasing in focus, this type of
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34 498 information could be particularly interesting for food industries that want to develop
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36 499 products with particular temporal sensory profiles for specific consumer groups, with
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39 500 different objectives (e.g. product optimization, products aimed at reduced intake, or
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41 501 products for elderly to increase their calorie intake or certain nutrients) .

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44 502 [For illustration](#), we have used [a](#) case study on yoghurt products based on an
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47 503 experimental design. This fairly simple data set allowed to better understand the
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49 504 product descriptions and how they related to consumer expectations. The efficiency of
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52 505 the proposed approach should be better demonstrated in future studies with case
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54 506 studies involving more complex products.

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715 **Figure Captions**

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2 716 **Fig. 1.** Expected satiety values of yoghurt samples for cluster 1 (left), 2 (right).

3
4 717 *Error bar represents standard error of the mean (SEM)*

5
6 718 **Fig. 2.** Liking values of yoghurt samples for cluster 1 (left), 2 (right).

7
8 719 *Error bar represents standard error of the mean (SEM)*

9
10 720 **Fig. 3.** MFA perceptual map based on sensory attributes for time intervals: beginning
11 721 (b), middle (m), end (e).

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13 722 *L-S1, S-S1: liking, expected satiety for cluster 1*

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15 723 *L-S2, S-S2: liking, expected satiety for cluster 2*

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17 724 **Fig. 4.** Temporal changes of expected satiety for cluster 1 (a) and 2 (b).

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19 725 *Solid lines: differences in expected satiety (when an attribute is checked vs. non-*
20 726 *checked) are significant at test level of 0.05*

21
22 727 *Dashed lines: differences in expected satiety (when an attribute is checked vs. non-*
23 728 *checked) are not significant at test level of 0.05*

24
25 729 **Fig. 5.** Temporal changes of liking for cluster 1 (a) and 2 (b).

26
27 730 *Solid lines: differences in liking (when an attribute is checked vs. non-checked) are*
28 731 *significant at test level of 0.05*

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30 732 *Dashed lines: differences in liking (when an attribute is checked vs. non-checked) are*
31 733 *not significant at test level of 0.05*

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Figure 1

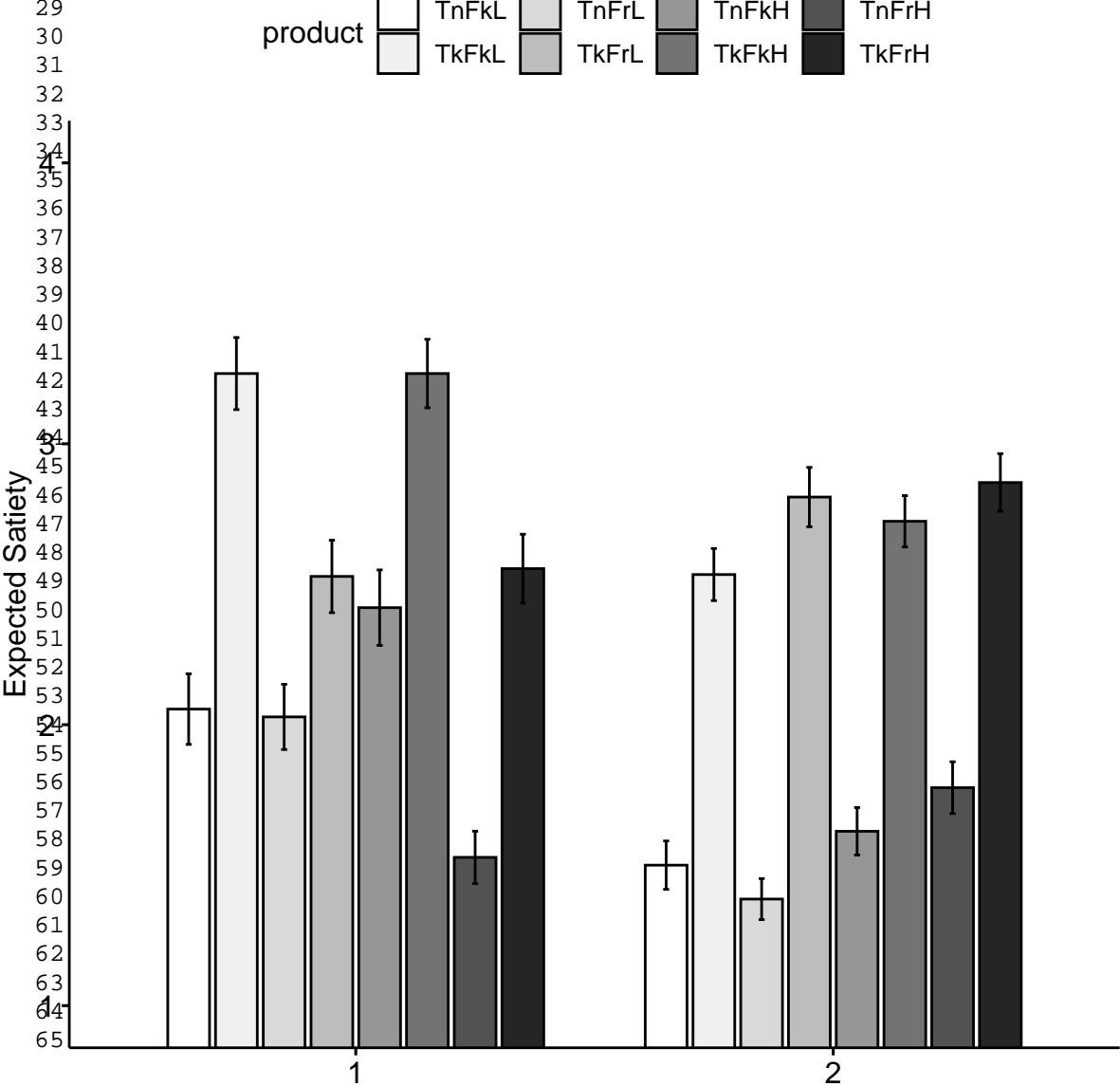


Figure 2

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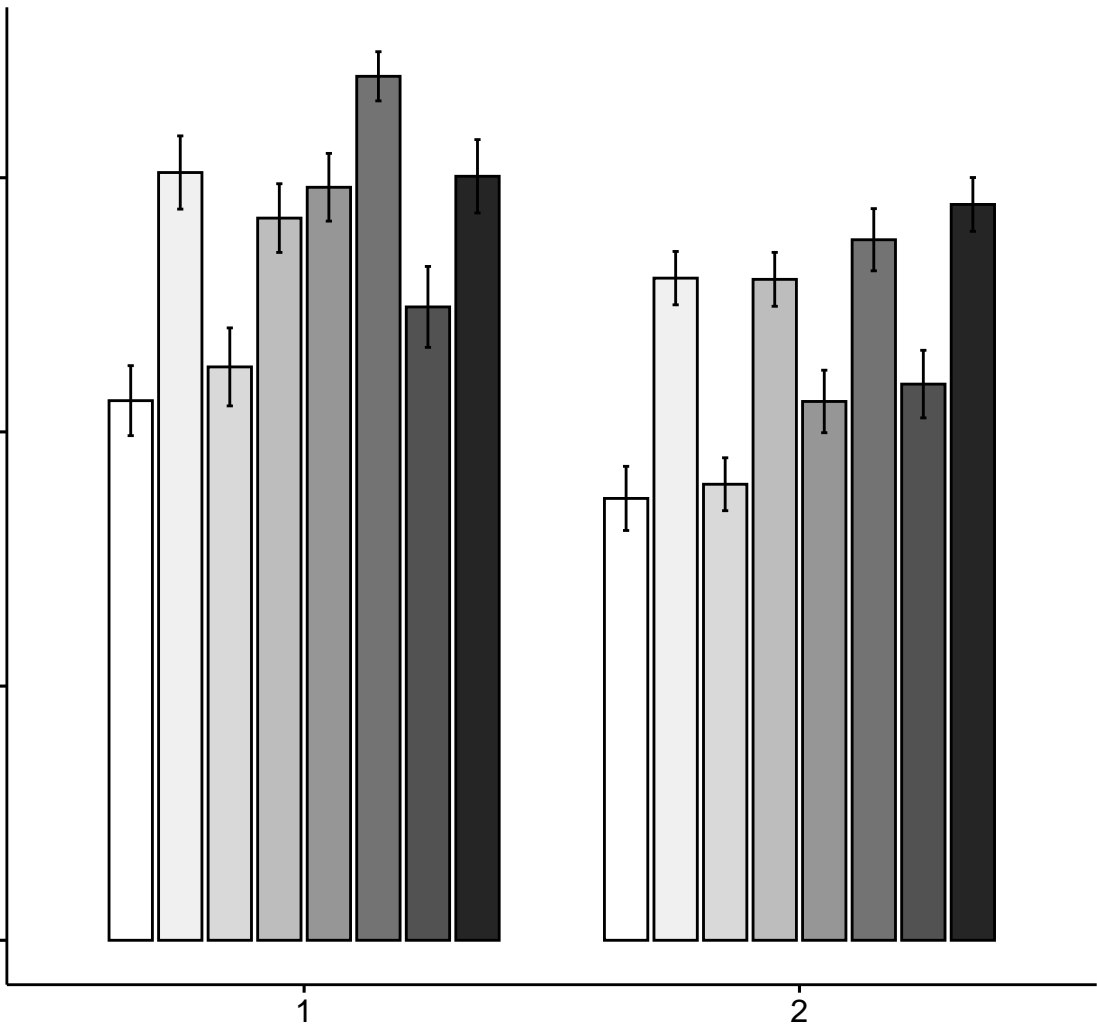
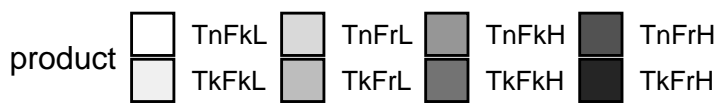


Figure 4a

Cluster 1 (n=36)

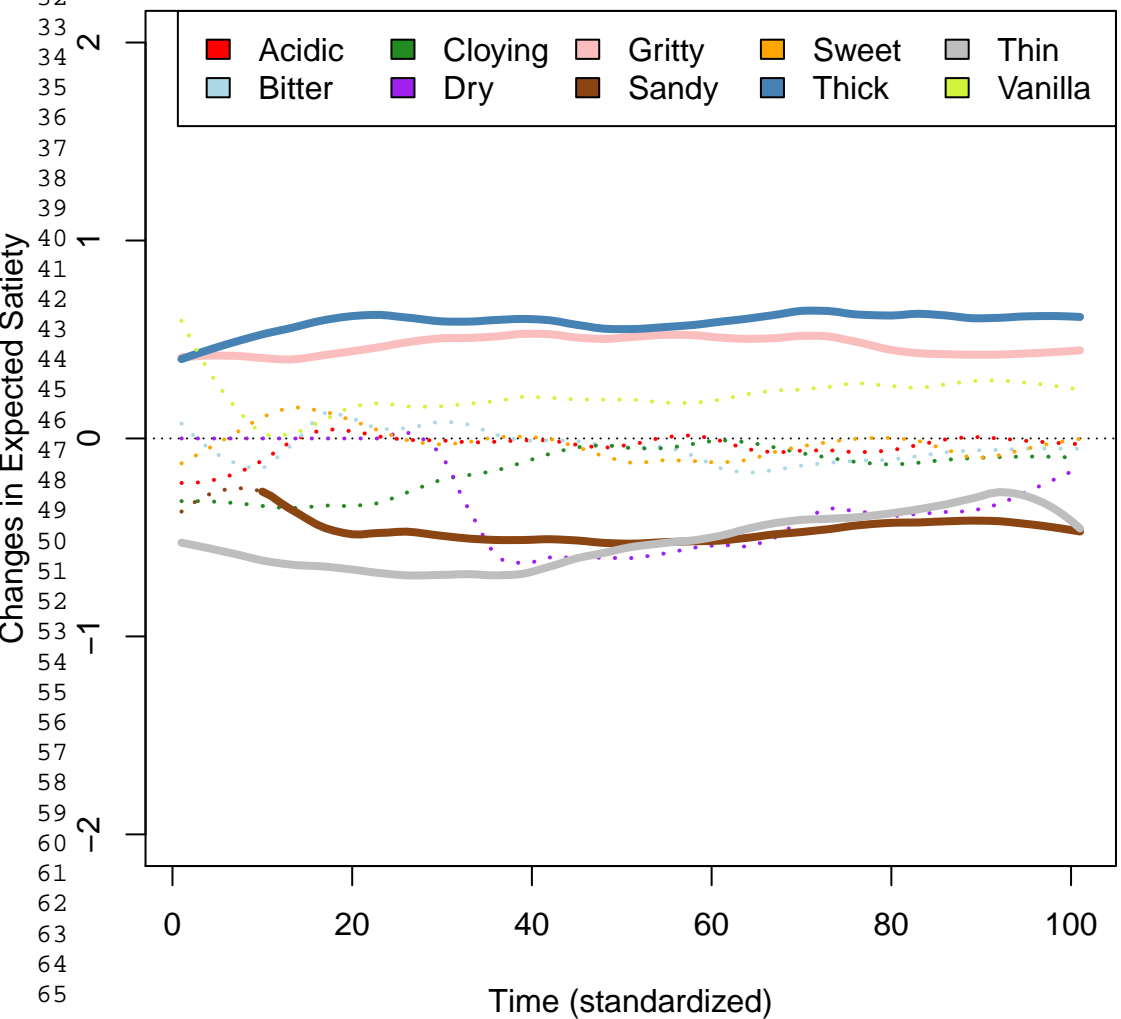


Figure 4b

Cluster 2 (n=58)

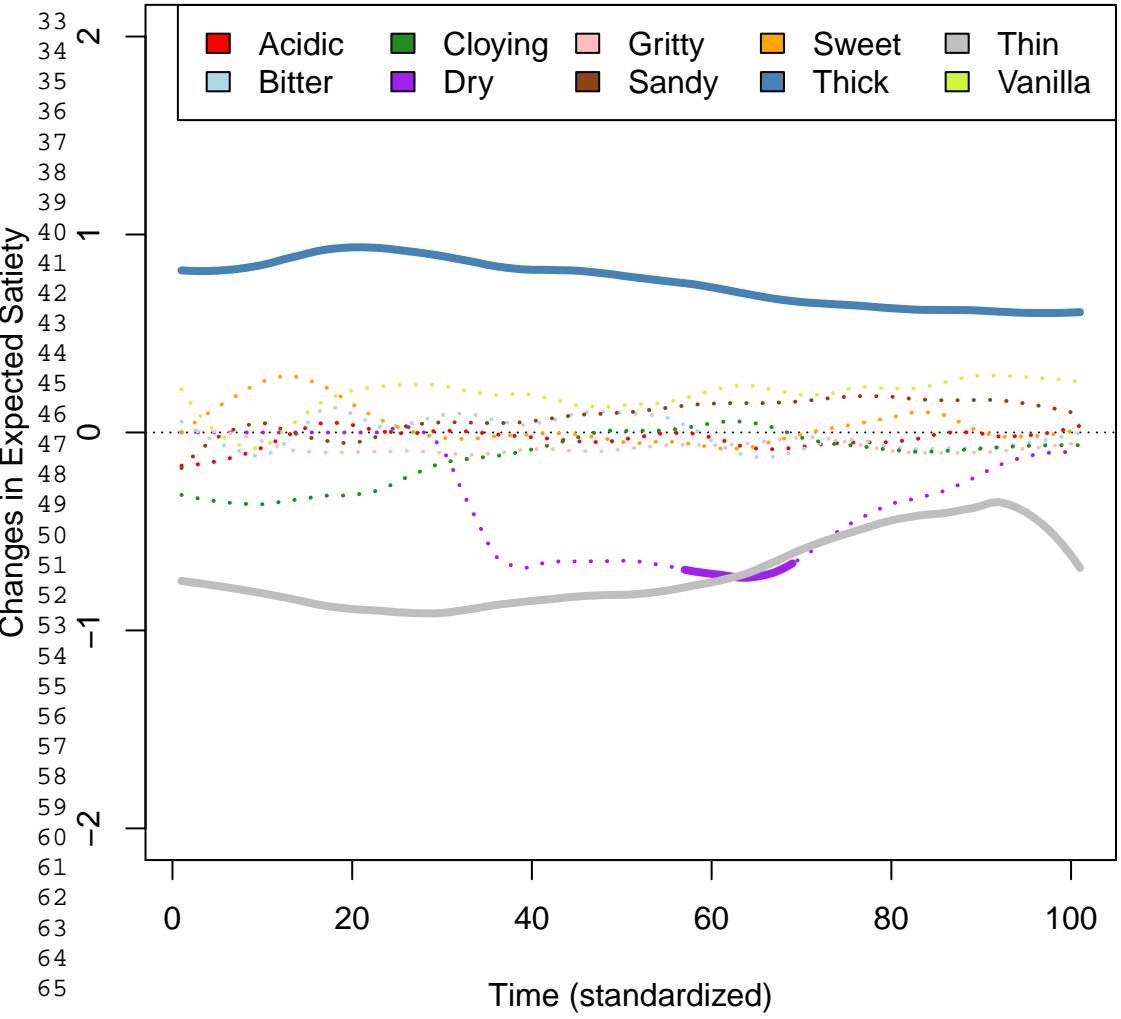


Figure 5a

Cluster 1 (n=36)

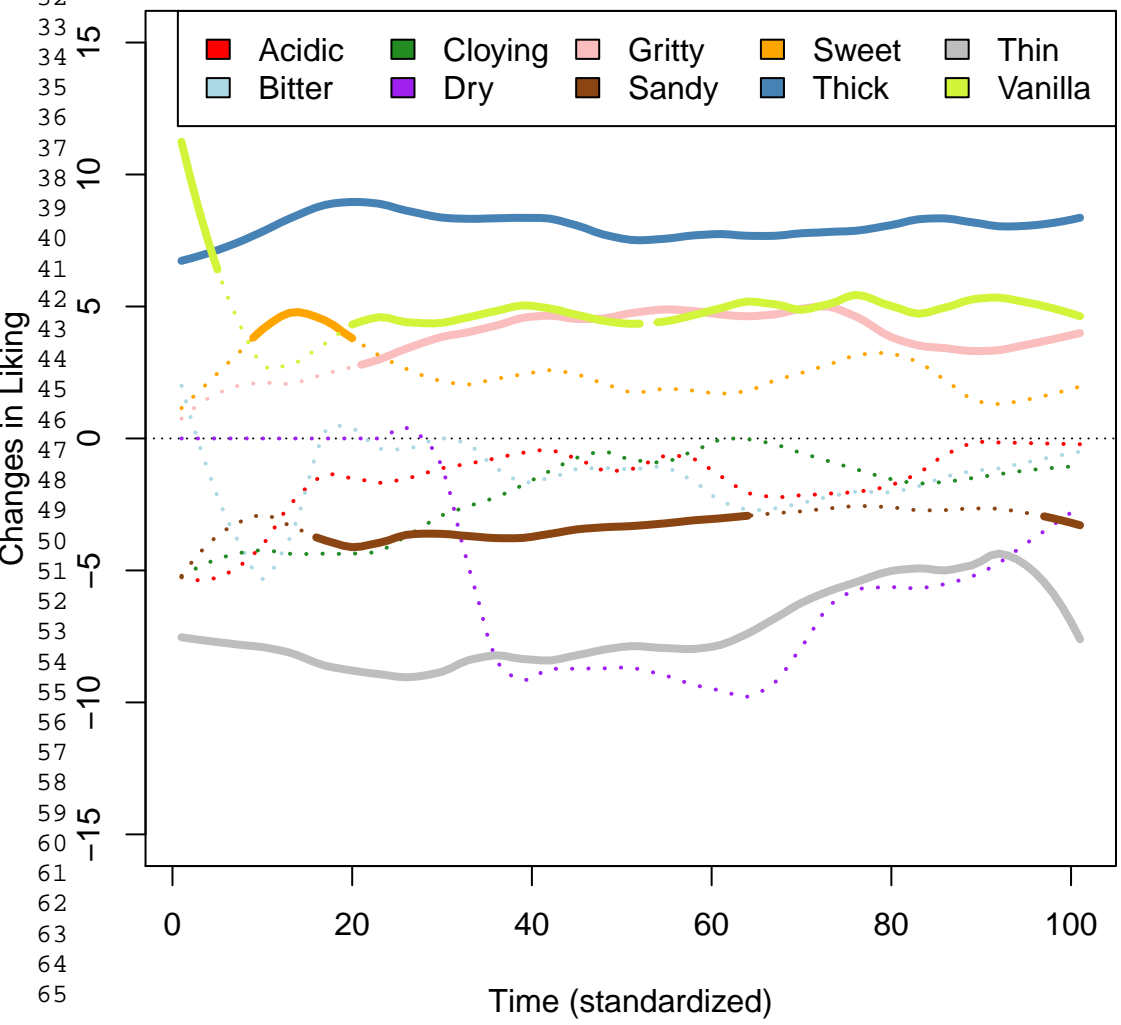
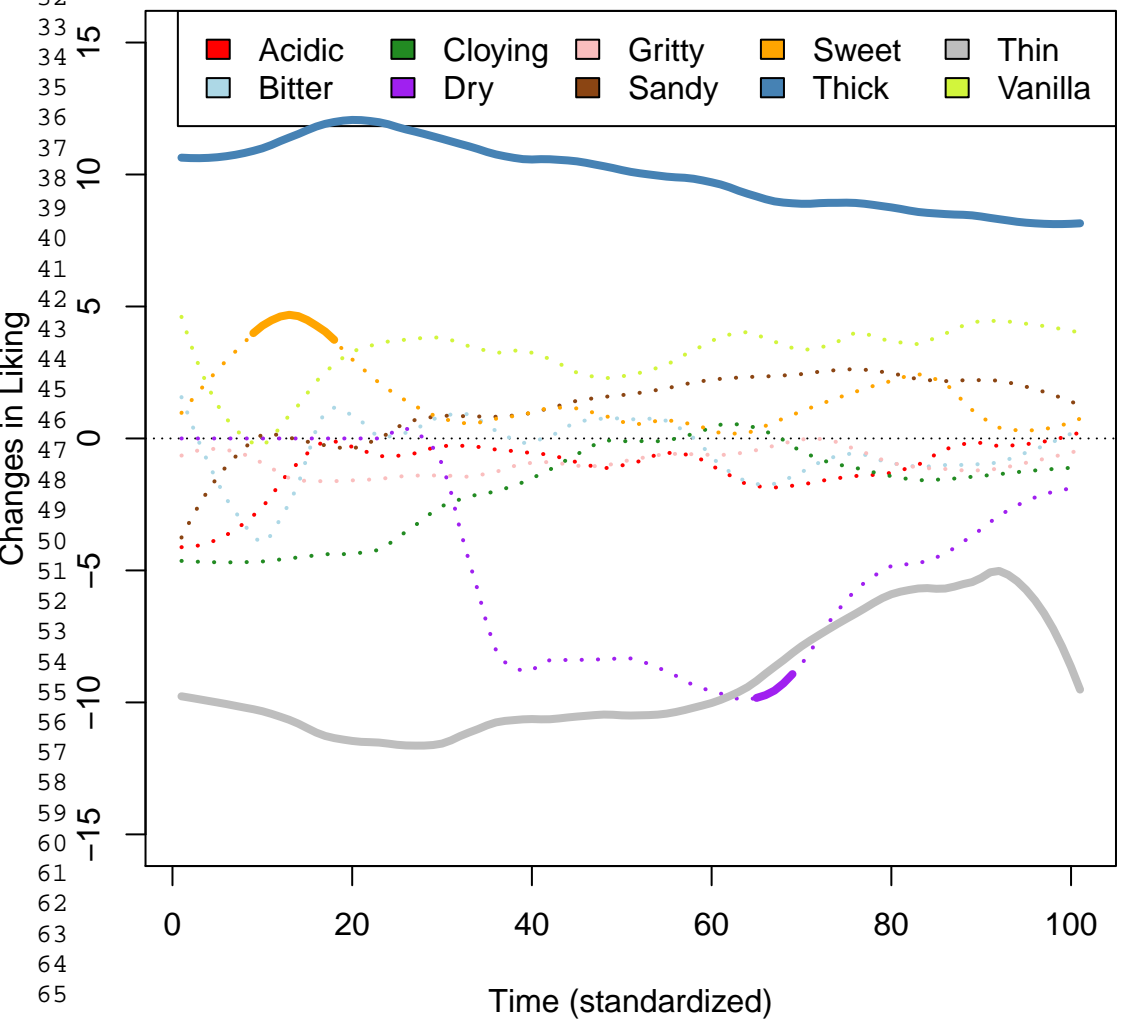


Figure 5b

Cluster 2 (n=58)



Conflict of Interest and Authorship Conformation Form

- All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.
- This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.
- The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript

Credit Author Statement

Quoc Cuong Nguyen: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Paula Varela: Conceptualization, Data curation, Formal analysis, Methodology, Writing – review & editing.