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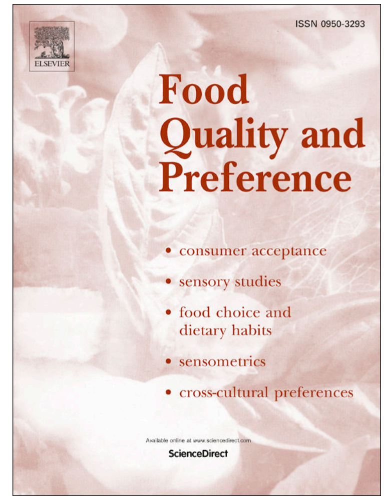

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Identifying temporal drivers of liking and satiation based on temporal sensory descriptions and consumer ratings

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Abstract

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

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

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

Penalty-lift analysis was used for each time point. Also, the false discovery rate (FDR) was applied to correct p-values for multiple tests responding to sequential time points. Differences were found related to how particle size attributes and flavour intensities drove liking for each cluster at different time points. For cluster 1, while Gritty was positive driver from the middle to the end, Sandy was negative driver in the middle; and Vanilla was positive driver of liking throughout the mastication. For cluster 2, only Sweet was pointed as positive driver at the beginning, and Dry as negative driver in some time points at the middle of the mastication.

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

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

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

1. Introduction

Dynamic sensory perception in food product development

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

Methods to investigate temporal drivers of liking (TDL)

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

Several approaches have been tested to determine which sensations are dominant when liking of a product increases or decreases (Silva et al., 2018). Thomas et al. (2015) have introduced the concept of *Liking While Dominant (LWD)*, calculated as the average of the n individual temporal liking scores while the attribute was dominant, to identify Temporal Drivers of Liking (TDL). If the LWD is significantly larger than the mean liking, the attribute can be considered as a positive TDL; if significantly lower, the attribute is a negative TDL. In the follow-up study, these authors have developed the method called Alternated Temporal Drivers of Liking (A-TDL) where temporal liking is alternated with TDS in the same session (Thomas, van der Stelt, Prokop, Lawlor, & Schlich, 2016), and the method called Simultaneous Temporal Drivers of Liking (S-TDL) in which consumers perform TDS and temporal liking simultaneously using the same data acquisition screen (Thomas et al., 2017). This approach has been shown as effective methodology for characterizing TDL; however, some points need to be considered carefully. First, analyzing the LWD data one assumes that the length of time an attribute is dominant affects liking (Carr & Lesniauskas, 2016). A potential drawback is that LWD calculation only focuses on the dominant attribute, while non-significant variables (in particular in case of small sample sizes) might be related to liking as well (Meyners, 2016). Second, this approach enables identification of drivers of liking for a certain product, not for all products. Lastly, it loses the temporality of drivers since temporal drivers of each product are identified by comparing LWD values with the mean liking over the quotations weighted by their durations.

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

Individual differences

In oral processing, the physiological aim is to produce a suitable bolus for swallowing; however, subjects have different strategies to obtain a swallowable bolus (Mishellany, Woda, Labas, & Peyron, 2006). More specifically, subjects have preferred ways to manipulate and manage food in mouth and this behavior determines the food texture they prefer; that is, the key drivers of liking and other expectations (Brown & Braxton, 2000; Jeltema, Beckley, & Vahalik, 2016). Recently, Varela, Mosca, Nguyen, McEwan, and Berget (2021) highlight that different groups of consumers are driven by distinct textural attributes when assessing liking and satiety, differently influencing their intake. Furthermore, Nguyen and colleagues speculated that dynamic sensory perception was key in defining satiety expectations (Nguyen et al., 2017) and that consumers with different eating styles would have different reactions to textural changes (Nguyen, Næs, Almøy, & Varela, 2020). Therefore, it is important to see how individual differences influence the relations between consumer ratings and dynamic sensory perceptions.

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

2. Materials and methods

2.1. Yoghurt data collection

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

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

2.2. Data analysis

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

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

When applied in the present paper, the clustering was aimed at identifying segments of consumers having highly correlated directions of expected satiety. In an attempt to set aside the "noise" consumers, an improvement of CLV clustering using the $K + 1$ strategy was applied (Dave, 1991). (Vigneau, Qannari, Punter, & Knoops, 2001). In particular, the "noise cluster" contains hidden consumers who are expected to have the same or low correlation, ρ, with all the observed consumers. The parameter ρ is selected according to the estimated communality (i.e. internal homogeneity criterion) H_k, the estimate of the effect size (i.e. discrimination ability) d_k (Vigneau et al., 2016).

The unbalanced nested ANOVA was applied on expected satiety, considering product (fixed effect), cluster (fixed effect), consumer nested within cluster (random effect) and interaction of product and cluster (fixed effect) as sources of variation. It is noted that the model would be unbalanced as the number of consumers in clusters could be different.

2.2.2. Multiple Factor Analysis (MFA) on aggregated data

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

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

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

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

For certain sensory attributes, randomization tests were applied in a large number of times (for example, 100 times in case of TDS or TCATA data with standardized evaluation time) to identify if the attribute affected the changes in liking (or expected satiety) significantly over time, resulting in a multiple testing. For this multiple testing, probability of a false positive in this scenario was now inflated and clearly required adjusting the original single test significance level of 0.05 (Balding, 2006).

Although a number of different multiple testing correction methods exist, the false discovery rate (FDR), proposed by Schweder and Spjotvoll (1982) and Benjamini and Hochberg (1995), has proven to be reliable as statistical criteria to determine the significance in high-dimensional testing (Strimmer, 2008). Rather than controlling the false positive rate, the FDR controlled the false discovery rate. Particularly, FDR was the expected proportion of false positives among all positives which rejected the null hypothesis and not among all the tests undertaken as shown in Eq. (1)

$$False\ Discovery\ Rate\ (FDR) = \ Expected\left(\frac{False\ Positive}{False\ Positve + True\ Positive}\right) \qquad (1)$$

In the FDR method, p-values were ranked in an ascending array and multiplied by m/k where k is the position of a p-value in the sorted vector and m is the number of independent tests (Jafari & Ansari-Pour, 2019). The interested reader is referred to Benjamini and Yekutieli (2001); Jafari and Ansari-Pour (2019); Strimmer (2008); Wright (1992) for detailed description of FDR and other correction approaches.

All analyses were carried out using R version 4.0.2 (R Core Team, 2020) with add-on packages ClustVarLV (Vigneau et al., 2015), lmerTest (Kuznetsova, Brockhoff, & Christensen, 2017), FactoMineR (Lê, Josse, & Husson, 2008), and EnvStats (Millard, 2013).

3. Results

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

3.1. Clustering of consumers according to expected satiety

The CLV clustering using the $K+1$ strategy started with the determination of number of clusters. Considering the aggregation criterion Δ, it was shown that the aggregation criterion fell when passing from a solution with three clusters to those of two clusters. This suggested that “unnatural” clusters were being merged, and therefore two clusters (K = 2) were retained for the subsequent analyses. The noise cluster was determined according to the threshold value ρ. In principle, it was selected to compromise between the number of discarded consumers and the expectation regarding the characteristics of the noise cluster. The threshold value ρ was selected based on the communality index (H_k) and effect size (d_k); particularly, the values of ρ leading to the smallest internal homogeneity (H_k) and the smallest discrimination ability (d_k) associated with the ‘‘noise cluster’’ could be singled out. Based on this, the ρ of 0.43 was chosen (data not shown). With the determination of number of clusters (K =

2) and threshold value (ρ = 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 related to the particle size. Thick samples were rated higher in cluster 1, but yoghurts with flakes (Fk) were rated significantly higher as compared to the flour ones (TkFkL > TkFrL, TkFkH > TkFrH). In particular, the expected satiety of thick-flakes samples (TkFkL, TkFkH) was found as significantly higher than the same samples for cluster 2.

As can be seen in Fig. 1, ratings of expected satiety of the products TkFrL and TnFkH were not significantly different in cluster 1. That indicates the influence of the interaction between two factors: viscosity (think vs. thin), and particle size added (flour vs. flakes) on ratings of expected satiety. This result is in agreement with the finding in our previous study (with the same data) in which, by applying PCA on expected satiety coupled with sensory description, Nguyen et al. (2020) highlighted that two main components, driven by particle-size and viscosity, explained the separation of these same products. Further explanation should be provided in the subsequent part when temporal drivers of expected satiety considered.

Hedonic ratings (liking) of the different products are depicted in Fig. 2. The results were generally in line with the results of expected satiety, but with some differences (the products being high in liking are high in expected satiety, and conversely). More specifically, there were two groups of products: thick products (TkFkL, TkFrL, TkFkH, TkFrH) and thin products (TnFkL, TnFrL, TnFkH, TnFrH), where thicker ones were generally better liked in both clusters. However, one of the thin samples was particularly well liked in cluster 1 (TnFkH), which was not the case in cluster 2. Liking and expected satiety followed similar patterns in cluster 2, but this was not so clear for cluster 1.

3.3. Temporal drivers of liking/ expected satiety for each cluster

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

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

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

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

For cluster 1, in addition to thickness perception, particle-size (gritty vs. sandy) and flavour (sweet, vanilla), attributes mainly correlated to the first component of the MFA, also contributed to the changes in liking (L-S1) and expected satiety (S-S1). Fig. 3 shows that while gritty perceptions during the mastication (*b.Gritty*, *m.Gritty*, *e.Gritty*) were positively related to L-S1 and S-S1 (i.e. increased liking and expected satiety of cluster 1), dry at the beginning (*b.Dry*) and sandy at the beginning (*b.Sandy*) as being negatively related. The flavour perceptions (*b.Vanilla*, *m.Vanilla*, *e.Vanilla*) led to an increase in liking (*L-S1*), but did not have very clear influence in expected satiety (*S-S1*).

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

Even if the MFA plot (Fig. 3) highlights some differences between clusters, the observation of the multidimensional space shows the vectors for both clusters pointing to the same quadrant, with the consequent difficulty of interpretation.

3.3.2. Drivers of liking and expected satiety based on the time continuum

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

Temporal drivers of expected satiety

Applying sequential penalty-lift analysis, Fig. 4 highlights the evolution of sensory drivers of expected satiety over time. The graphical display suggests *Thick* as a positive driver of expected satiety, while *Thin* results in lower expected satiety for both clusters, consistent with the previous findings based on time intervals.

The main differences between clusters were regarding the influence of particle-size (*Gritty* vs. *Sandy*). Cluster 1 associated gritty texture with higher satiety and sandy texture with lower satiety, but this association was not found in cluster 2. It is worth noting that they were significant over all consumption time (i.e. from the beginning to end of the eating process). In cluster 2, *Dry* was found to be a negative driver during T55-T70. To a certain extent, these results here are more straightforward to interpret as compared with the display in which sensory perceptions were considered on different time intervals (Fig. 3). These results, based on time continuum, demonstrate that consumers in cluster 1 considered both thickness and particle-size variables when they rated expected satiety, whereas consumers in cluster 2 focused on thickness only when they rated their expected satiety. Moreover, similar to the drivers based on time intervals, flavour perceptions did not play a significant role in any of the clusters.

Temporal drivers of liking

The sequential penalty-lift analysis applied to the liking data (Fig. 5) shows the temporal drivers of liking for cluster 1 and 2. Thickness was the major driver of liking for the two clusters; particularly, *Thick* increased whereas *Thin* reduced hedonic ratings. Similar to the expected satiety results, the influence of thickness (*Thick* vs. *Thin*) on liking occurred throughout all the eating process.

For cluster 1, *Gritty* and *Sandy* led to high and low hedonic ratings, respectively. *Gritty* was a strong driver of liking from the middle to end of the evaluation (T20-T100), while grittiness at the beginning was not significantly associated with a higher liking (T0-T20). Meanwhile, *Sandy* showed up as negative driver at the middle only (T20-T60), decreasing the liking if present during this time. At the end of the evaluation, *Sandy* appeared as a negative driver in some time points.

Regarding flavour attributes, the temporal drivers of liking shown in Fig. 5 indicated that liking was associated with sweet perceptions (*Sweet*, *Vanilla*). As can be seen, the effect of *Vanilla* on liking was strongest at the beginning, and gradually declined until T10. After that, *Sweet* appeared as the main taste that increased liking (T10-T20). Finally, *Vanilla* appeared again as positive driver of liking until the end of the consumption. In general, both *Sweet* and *Vanilla* can be considered as positive drivers of liking.

For cluster 2, the drivers of liking were quite clear. In addition to *Thick*/*Thin* attributes as positive/negative drivers over time, it was shown that *Sweet* increased liking only at the beginning (T10-T20) similarly to cluster 1. Unlike cluster 1, in some time points at the middle (T55-T70), *Dry* was a negative driver of liking.

4. Discussion

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

4.1. Flavour as a driver of liking and expected satiety

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

The proposed new approach, based on the whole temporal curve, highlights sweetness as a driver of liking in the beginning of the oral processing for both clusters and vanilla as a relevant driver during almost all consumption for cluster 1. This is more in line to what is expected for these kind of products (sweetness as a positive driver) and could mean that considering the whole curve gives more "granularity" to the results, allowing for a better interpretation. The fact of sweetness being important at the beginning of the consumption can be especially relevant in this category, as yoghurt is typically expected to taste acidic, but a certain level of sweetness is required, and seemed to be most important in the beginning, at least for the yoghurts and consumers in this study. Although unveiling more detailed results, the sequential penalty-lift analysis plots, however, are not that easy to communicate outside of the sensory and consumer science community, which can be a disadvantage at the time of taking action from the results. One could envision then, a potential combination of both data analyses approaches, with different levels of granularity and different applications in terms of results communication. Future work should perhaps look into easier ways of displaying the sequential penalty-lift results.

4.2. Individual differences underlying liking and expected satiety

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

Investigating the influence of viscosity and particle size added on oral processing behavior, Mosca et al. (2019) highlight that while a decrease in yoghurt viscosity did not significantly affect eating rate and *ad libitum* intake, a decrease in granola particle size decreased spoon size, eating rate and *ad libitum* intake without affecting liking. It is important to note that these results were obtained without considering individual differences among consumers. Contrary to the above results, some research highlighted that increases in viscosity decreased intake of semi-solid foods (de Wijk, 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 *Smooshers* 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 give importance to this attribute to rate expected satiety and liking between the products tested.

The results here suggest the important role of tactile sensitivity (grittiness in this case) in determining drivers of consumer liking and satiety-related perceptions. Similar results have been also observed in the research by Puleo, Miele, Cavella, Masi, and Di Monaco (2019) in which high-graininess-sensitive consumers liked more the most refined samples as compared with moderate- and low-graininess-sensitive consumers.

These findings highlight the importance of further understanding texture/tactile sensitivity on preferences, expectations of satiety, and food intake as previously reported by Forde and Delahunty (2002) and more recently by Puleo et al. (2019). While the importance of texture in food preferences is well documented, there is a limited understanding how physiological individual differences in sensitivity would influence texture perception which in turn impact consumer preferences, expectations of satiety and food intake. More research should be performed to investigate these relations, and how those are related to dynamic sensory perceptions.

5. Conclusions

This paper proposes a novel method to explore temporal drivers of consumer perceptions and expectations, liking and expected satiety, but could potentially be applied to other perceptions or expectations that are influenced by temporal sensory perception. This method relies on converting temporal data into CATA-coded data for each time point, applying penalty-lift analysis sequentially to identify sensory drivers, and combing these drivers into temporal driver curves. As compared to temporal drivers based on time intervals, this method, based on the full time continuum, allowed us to see the evolution of sensory drivers over time while maintaining the temporality of the data, and allowing for a more detailed interpretation. Coupled with clustering of consumers, this approach can provide new insights for better understanding how temporal perception influences consumers choices.

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

For illustration, we have used a case study on yoghurt products based on an experimental design. This fairly simple data set allowed to better understand the product descriptions and how they related to consumer expectations. The efficiency of the proposed approach should be better demonstrated in future studies with case studies involving more complex products.

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Figure Captions

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

Error bar represents standard error of the mean (SEM)

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

Error bar represents standard error of the mean (SEM)

Fig. 3. MFA perceptual map based on sensory attributes for time intervals: beginning (b), middle (m), end (e).

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

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

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

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

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

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

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

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

Highlights

- A panel described temporal perception and consumers rated liking/expected satiety.
- Two clusters of consumers were retained according to their expected satiety.
- Penalty-lift analysis applied to sequential time points to find temporal drivers.
- Textures differently impact satiety expectations in two groups of consumers.
- Particle size attributes (Gritty vs Sandy) were found to be important classifiers.

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.