Individual differences underlying food intake and liking in semisolid foods

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ABSTRACT

Many sensory, cognitive, and physiological factors contribute to satiation and satiety responses; sensory and cognitive factors lead to feelings of satiation and short-term satiety. This research aims at understanding how sensory perception and consumer preferences are related to food intake of semisolid foods, using a case study on yogurt with controlled texture variations. Individual differences in food intake and liking were analyzed together with eating rate, to get a holistic picture of the sensory drivers of liking and intake in different groups of consumers. Six yogurts were formulated based on a design of experiment to obtain isocaloric products varying in consistency and particle size. Samples were evaluated by a trained panel via Quantitative Descriptive Analysis (QDA) and Temporal Check-all-that-apply (TCATA).

Additionally, 103 consumers ate ad libitum the yogurt samples and rated their liking. Amount eaten was measured by weight and eating rate via video recording. The effect of particle size on intake depended on the thickness of the matrix. Based on Principal Component Analysis (PCA), three groups of consumers were identified that reacted differently to the changes in yogurt texture in terms of amount eaten and liking responses. While for some consumers liking and intake were correlated, others ate more of what they liked less, driven by textural changes in the matrix. Results suggested that different patterns in intake and liking may be related to different eating styles, thus, manipulations on textural properties may reduce the intake for some consumers, but not for all. This work unveils the importance of studying individual differences when measuring food intake, together with static and dynamic sensory drivers for different segments of consumers. In a time where food personalization increases in focus, it seems possible to reformulate food texture to influence consumers expectations and intake, aiming at targeting overeating; however, individual differences need to be better understood to know the implications for different groups of consumers.

Keywords*: individual differences, oral processing, texture, eating behavior, intake, sensory drivers, temporal perception*

1. INTRODUCTION

Understanding the extent to which food properties affect the amount of food consumed within a meal is of great interest. Texture has been identified to have a significant impact on satiation (Hogenkamp et al., 2011), with products that require more oral processing efforts being associated to lower *ad libitum* intake (de Wijk et al., 2008; Zijlstra et al., 2009; Ferriday et al., 2016; Lasschuijt et al., 2017; McCrickerd et al., 2017). Forde et al. (2013) observed that among 35 foods representing a wide range of textures, foods consumed with smaller bites, higher number of chews and longer oral exposure time were associated with higher expected satiation. Similarly, the consumption of pre-packed meals at slower eating rates, longer pauses between bites and longer oral exposure time imparted higher expected satiation, greater post-meal fullness and greater satiety, suggesting that eating rate can affect how much is consumed within and between meals (Ferriday et al., 2016).

Many studies have reported how the modulation of textural properties can affect the satiating capacity of foods (Zijlstra et al. 2009; Bolhuis et al., 2014; Lasschuijt et al., 2017; McCrickerd et al., 2017). Bolhuis et al. (2014) observed that hard versions of hamburgers and rice salads were consumed at a 32% slower rate and 16% in lower amounts than the equivalent soft versions. In a study conduct by Tarrega, Marcano & Fiszman (2016), a 2.6-fold increase in the viscosity of yogurts increased expected satiation of yogurts by 28%. The addition of lyophilized pineapple cubes to yogurts further increased the expected satiation of low viscosity yogurt by 23% and of high viscosity yogurt by 6%. McCrickerd et al. (2017) observed that a thicker porridge, which was consumed slower, with larger bite size, longer oral exposure time per bite and more chews per bite, had an approximately 12% lower intake than a thinner version of similar composition. Using combinations of iso-caloric yogurts varying in the viscosity of the yogurt matrix and in the size of granola pieces, Mosca et al. (2019) observed that a 2-fold decrease in the size of granola particles (from 12 to 6 mm) added to yogurts, increased the number of chews by 7% and decreased eating rate by 7%, sip size by 6% and intake by 5% (which corresponded to 17g) without affecting liking and familiarity. Morell, Fiszman, Varela, and Hernando (2014) showed that differences in dynamic perception in mouth influenced satiety expectations even in semisolid products of similar consistency. The use a dynamic/temporal technique to investigate texture perception during consumption will then allow for a better understanding of how differences in texture influence the satiating capacity of foods. In a study that compared barley breads varying in textural properties, Nguyen et al. (2017) identified the dynamic aspects of texture perception that were the drivers of satiety and satiation expectations using Temporal Dominance of Sensations (TDS). The dominance of chewiness in the first stages of mastication and coarseness throughout the mastication were related to higher expected satiety & satiation while the dominance of dryness and crumbliness at the beginning mastication were related to lower expectation of satiety &

satiation. Added to this, in a study on yogurts with addition of cereals, Nguyen et al. (2018) showed that sensory perception of attributes related to the oral process might affect satiety perception in different directions for groups of consumers with differentiated mouth behaviors. This highlights that there may be individual differences in how consumers respond to variations in texture, and that the influence of texture on satiation and food intake may not be the same for all consumers.

The current study aims to explore individual differences in drivers of liking and satiation through the combined analysis of eating behavior, liking, eating rate, food intake and both static and dynamic sensory perception. Data obtained in this study will allow a better understanding of food intake dynamics, which can contribute to the health and well-being of consumers.

2. MATERIALS & METHODS

Eating behavior was characterized through the observation of video recording of consumers while they normally ate the samples under investigation. Perceptual aspects of the corresponding samples were evaluated by obtaining the static and dynamic sensory profiles, by a trained panel, via Quantitative Descriptive Analysis (QDA) and Temporal Check All that Apply (TCATA). These sensory aspects were then related to direct measurements of food intake (*ad libitum*) by consumers and their subjective hedonic response to the samples (overall liking).

2.1. Test products

Six yogurts with added granola were tested as previously described by Mosca et al. (2019). A 2x3 full factorial design was used with 2 yogurt viscosity conditions (thin/thick) and 3 granola particle size conditions (small/medium/large). Granola was added to yogurt at a proportion of 15% w/w. All six samples had the same ingredient composition and calorie content.

The commercially available Optimel Greek style yogurt – natural (FrieslandCampina, NL) was used as thick yogurt. By stirring this product in a mixer, viscosity was reduced by approximately 1.7-fold. A commercially available granola (BioFamilia, Switzerland) was sieved to obtain granola pieces differing in size (medium: ~6mm and large: ~12mm). To obtain small granola pieces, granola was milled in a food processor (model Cuisine Système 5000, Magimix, France) for approximately 1 min and sieved. Pieces that passed through a 2.0 mm sieve were classified as small.

2.2. Characterization of eating behavior

This study was performed at Wageningen University, Wageningen, The Netherlands. A total of 103 Dutch participants (76 females, 27 males, average age: 21±3 yrs; average BMI: 21±2 kg/m^2) completed the study. All participants were regular consumers of yogurt (defined as consuming yogurt products at least once a week). Medical ethical approval for this study was obtained from the medical ethical committee of Wageningen University (NL62080.081.17).

2.2.1. Ad libitum intake, eating rate and liking

Six sessions were performed at breakfast time, in which participants (in a fasted state) consumed a yogurt sample served *ad libitum* while being video recorded. Participants received 1 Kg of product (850 g yogurt with 150 g granola; total energy content per serving was 1149 kcal) in 2 L ceramic bowls coded with 3-digit random numbers. The presentation order of the yogurts was balanced over participants and sessions using a modified Latin square design. Consumers were requested to eat the samples until feeling pleasantly full. A metallic tablespoon was used for the consumption of the samples. The amount of yogurt consumed was calculated as the difference between the initial and final weights of the bowl. Liking was rated after the consumption of the first spoon on a 100 mm VAS anchored “not at all” and “very much”.

To obtain eating rate and other oral processing parameters from the video recordings, a coding scheme was developed using the Observer software version XT 11 (Noldus Information Technology, the Netherlands). The frequency counts of spoons, chews and swallows and measures of total eating duration (min), total oral exposure time (period of food in the mouth) (min), and inter-spoon interval (period of no food in the mouth) (min) were directly extracted from the videos. Total oral exposure time comprised the summed time between the placement of a spoon in the mouth and the last swallow of each spoonful, while inter-spoon interval comprised the summed time between a final swallow and a subsequent spoonful. Eating rate (g/min) was calculated as the amount of food (g) consumed (*ad libitum* intake) over the total oral exposure time (min). More detailed information about this experimental procedure can be found in Mosca et al. (2019).

2.3. Characterization of static and dynamic sensory profiles

QDA and TCATA tests were performed by the trained panel at Nofima, Ås, Norway. The sensory tests were conducted in standardized individual booths following the ISO standards (ISO 8589, 2007). A total of 9 female assessors participated in the QDA test and 7 female assessors participated in the TCATA test. All assessors are part of Nofima’s trained panel and have extensive experience with both techniques.

Participants received 30 g of each yogurt in plastic containers coded with 3-digit random numbers. Samples were presented in a sequential monadic manner following a balanced presentation order. For both QDA and TCATA, no time restriction was imposed for consumption and samples were expectorated after evaluation.

2.3.1. Quantitative descriptive analysis (QDA)

To describe the 6 yogurt samples, generic quantitative descriptive analysis, based on QDA®, was performed, as described by Lawless & Heymann (2010). A 1-h pre-trial session was performed using extreme samples (thin yogurt-large granola particles and thick yogurt-small granola particles) for development and agreement on the descriptors and definitions by the assessors. After a 1-h pre-trial session, the descriptors and definitions were agreed upon by the assessors; all assessors were able to discriminate among samples, exhibited repeatability, and reached agreement with other members of the group. The final list was comprised of 5 odor attributes (acidic, sweet, metallic, roasted, sour), 4 taste attributes (sweet, acidic, bitter and sour), 4 flavor attributes (metallic, roasted, sour, cloying) and 7 texture attributes (crispiness, fullness, airiness, creamy, coarseness, sandy, gumminess). Samples were assessed in duplicate for the QDA test. Data collection was done using EyeQuestion (Logic8 BV, The Netherlands).

2.3.2. Temporal check all that apply (TCATA)

In TCATA, multiple attributes can be selected and unselected in the course of the evaluation, giving as output the trajectory of sensorial changes during oral processing (Castura et al., 2016). In a study that evaluated yogurt samples varying in textural properties, Nguyen, Næs & Varela (2018) reported TCATA as the technique that resulted in a more detailed sample description in terms of number of discriminating attributes, particularly when aiming at describing food satiating properties. TCATA was conducted as described by Nguyen et al. (2018). In a preliminary session, the assessors agreed upon the attributes that were more relevant to describe the temporal aspects of the samples. The TCATA list included ten attributes: taste (sweet and acidic), flavour (cloying) and texture (crispiness, fullness, airiness, hard, coarseness, sandy, gumminess). The attributes were revised by the assessors prior to the evaluation for familiarization with the distribution of the attributes on the computer screen. Assessors were asked to select all the attributes that were applicable to describe the sensory characteristics of samples at each moment of the evaluation and to unselect the ones that were no longer applicable. Samples were assessed in triplicate in the TCATA test. Data collection was done using EyeQuestion (Logic8 BV, The Netherlands).

2.4. Data analysis

All data analyses were performed in R, version 3.6.1, with the packages SensMixed, FactoMineR, ggplot2, tempR (for smoothing TCATA) (Kuznetsova et al., 2018; Le et al., 2008; Wickham, 2016; Castura, 2018).

2.4.1. Analyzing QDA and TCATA

Two-way mixed model ANOVA with assessor (random) and product (fixed) effects and their interaction was used for identifying which attributes distinguished between the products and to look at potential panel performance issues. Tuckey post hoc test was used for comparing the attribute means for different products. Principal Component Analysis (PCA) with non-standardized data was used to have an overall picture of the perceptual space.

Data from TCATA were time standardized and smoothed using the R-package tempR (Castura, 2018).

2.4.2. Mixed model ANOVA for consumer responses

Mixed model nested ANOVA was applied to test differences between products. Intake, liking and eating rate were modelled as effect of product (six levels), gender, their interaction and the subject within gender as a random effect. For further insight, the product effect was split into Granola (three levels) and Viscosity (2 levels), leading to the model

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \alpha\beta_{ij} + \alpha\gamma_{ik} + \beta\gamma_{jk} + S(\gamma) + \varepsilon_{ijk} \qquad \text{(Eq. 1)}$$

Here α, β and γ represent viscosity, granola size and gender effect respectively. The S(γ) is the subject within gender effect. The model was fitted using lmer in the R-package lmerTest (Kuznetsova et al., 2017), whereas least square means and their standard errors were computed and testing using the emmeans package (Lenth, 2019). Terms were considered significant for p-values below 0.05.

2.4.3. Individual differences in intake, liking and eating rate

Principal component analysis (PCA) was applied for QDA (panel averages), intake, liking and eating rate, in the same manner. The data was organized as a matrix with the products on rows and the measurement for the consumers on the columns. After centering and standardizing each column to account for individual use of scale, the 6x103 matrix was then input for PCA. PCA is a method for dimension reduction and is widely used for data exploration when there are multiple variables. When PCA is performed on consumer liking data, this is referred to as preference mapping. The components must be interpreted using knowledge about the products for the study (here the experimental design). The direction of consumers in the loading plot, indicate the preferred directions for the products. In this paper the approach commonly used for preference mapping (PCA) was applied for intake and eating rate, to get an easy visualization of how products differ with respect to these measurements. Based on the consumer loadings for the PCA on intake, segmentation of consumers was done from visual inspection of the PCA plots as described in Endrizzi et al. (2014).

The Pearson correlation between intake and liking was computed for each consumer. To compare the multivariate structure of the datasets, the RV coefficient (Robert and Escoufier, 1976) was computed between pairs for product maps for the two-dimensional PCA plots.

Intake was related to sensory properties of samples similar as in external preference mapping, more specifically the vector model (McEwan, 1996) was fitted for each consumer intake to the first two principal components for the PCA. These analyses are referred to as “intake mapping” in the results below.

Differences in eating rate and liking for segments identified from the intake, were analyzed through a mixed model where the eating rate or liking was fitted to a model with product, gender, segment effect and their interactions.

The evaluation duration in temporal data were split into shorter time intervals (T0-T40: beginning, T41-T80: middle, T81-T100: end), and scores were the average of the scores given to an attribute during an evaluation weighted by their duration. Temporal drivers of liking and intake were studied by plotting the dynamic sensory attributes (TCATA) across all oral processing intervals (beginning, middle and end), via MFA, and overimposing liking, intake and eating rate for the three segments as supplementary variables.

3. RESULTS

3.1. Sensory description of yogurts

3.1.1. QDA

The sensory analysis by QDA revealed that sensory properties of yogurts with small granola were significantly different from large and medium, both for thick and thin yogurts (ANOVA, data not shown, but available for the interested reader by contacting the authors). Textural properties were the most important for describing differences between samples, but there were also significantly differences for flavor components. Thick yogurts were described as creamier and fuller, whereas thin yogurts where airier. Yogurts with small granola were significantly sandier than the ones with large and medium granola. In addition, they were perceived as having more cloying flavor, as well as sweeter and more roasted in odor. The perceptual space as highlighted by the PCA analysis is shown in Figure 1.

Insert Figure 1. Around here

3.1.2. TCATA

The six samples were very different in their dynamic profiles, some attributes appeared only for one type of sample throughout the oral process (e.g. airy in thin yogurts, full in thick ones, etc.). Figure 2 presents the dynamic characteristics of the samples plotted by attribute, for easiness of interpretation. Small granola samples were perceived as sandy throughout the consumption, but mostly towards the end. Meanwhile, yogurts with large particles were perceived as crispy mainly in the beginning and middle of the consumption and coarse in the middle to end. Medium and large granola particles imparted hardness in the beginning and gumminess in the end. It is worth noting that particle size also imparted taste: small granola was perceived as less acidic and as sweeter than the samples with larger sizes; smaller particles of sugary components in the granola may be better suited for a quicker solute of tastants to be transported to the taste buds.

Please insert figure 2 around here

3.1.3. Effects of yogurt viscosity and granola particle size on intake, liking and eating rate

Linear Mixed Models (LMM) were applied to estimate the effect of physical properties on intake, liking and eating rate (Table 1). Overall, the smallest granola was the least liked, was eaten in the smallest amount but had the fastest eating rate (Figure 3). Yogurt viscosity had highly significant ($p<0.0001$) effect on intake and eating rate, with larger intakes and faster eating rates for thin yogurts (Figure 3). Thin yogurt samples were significantly eaten more and faster. Thick yogurts were, however, slightly more liked ($p=0.05$). The effect of particle size on the intake depended on the thickness of the matrix; more specifically, the intake of yogurts with small granola was significantly lower in thick as compared to thin yogurts. With regards to liking, there was no significant interaction between yogurt viscosity and granola particle size. In general interactions between gender and product factors (viscosity and granola) were not significant, although some trends for significant interactions were observed for intake (Table 1).

Insert Figure 3 around here

3.2. Correlation of intake (amount eaten) and liking

RV coefficients were computed to compare PCA scores plots (PC1-PC2) for PCA on QDA data (Figure 1), intake, liking and eating rate. There was significant multivariate correlation between intake and liking (RV = 0.64), but not between QDA and intake (RV =0.17), nor between QDA and liking (RV = 0.36). For liking and intake, the differences between large and medium granola seemed to more evident than for the QDA results, this can be due to the fact that smaller granola also imparted flavor to the samples, and the first component of the QDA reflected those differences (small vs medium/large). Thus, QDA probably focused on more (or different) attributes than those that could drive the intake. Eating rate, and consequently intake have been found to be mostly influenced by texture, rather than flavor (Hogenkamp et al., 2011).

Based on the RV coefficients between the scores from Liking and Intake (RV = 0.64) there was overall a trend that intake was higher for the more liked products. There were, however, individual differences in the Pearson correlation between liking and intake. The correlation widely varied, between -0.98 and 0.92 with an average of 0.20 and the median equal to 0.30. Correlation was significantly larger than zero for approximately 20% of consumers. Surprisingly, some consumers showed a significant negative correlation between intake and liking, which meant they eat more of products they reported to like less. This shows there was something driving them to eat more of these products. Figure 4 shows the correlation loadings from PCA of the intake. Different consumers are represented by dots where color and size reflect the correlation between liking and intake. There is a tendency for higher positive correlation in the lower right corner of the map, but one can see there is a good spread.

Insert Figure 4 around here

3.3. Individual differences in intake (amount eaten)

To better understand individual differences in intake, three groups of consumers were identified in the PCA plot for the intake (Figure 5a). These three groups reacted differently to the yogurt texture in terms of amount eaten (Figure 5b). The first segment had an increased intake of yogurt with small granola and will be referred to as “small eaters”. The second segment showed a decreased intake of thick yogurts with small granola as compared to large granola particles, whereas for thin yogurts their average intake was comparable for all particle sizes; hence, this group is referred to as “thick sensitive” consumers. The last group had a lower intake of yogurt with small particles for both thick and thick yogurts. The intake of medium and large granola was at the same level. This latter group is referred to as “small rejectors”.

Insert Figure 5 around here

3.3.1. Intake mapping

Average intake for each cluster was related to the sensory properties of the yogurts in the same way as in an external preference mapping. In Figure 6 the sensory loadings of the attributes profiled by QDA are shown together with the loadings for each segment in an “intake map”. The average of the “small eaters” intake and eating rates, correlate with attributes such as sandy, sweet, cloying and roasted, but in opposite direction to their liking, that was correlated to attributes like crispy, gummy or coarse. This clearly shows that the small particles were related to an enhanced eating rate, larger intake, even if they did not like those products. For “small eaters” thick/thinness of the yogurt was not so relevant for either liking or eating behavior. The average of the intake of the “thick-sensitive” points in the direction of airy, not correlated to their liking and partially with their eating rate. For these consumers, intake seemed to be driven by the easiness to process the thin (airy) yogurts with smaller particles, however, liking was driven by large particle sizes and disliking of small. Thus, when small particles (disliked) were together with thick yogurt, intake dropped. For “small rejectors” liking and intake were directly correlated, and driven by attributes imparted by large particles like gummy, crispy, etc. Even if eating rate was also driven by thin yogurt and small particles for these consumers, intake was totally driven by liking, regardless of the texture.

Insert Figure 6 around here

3.3.2. Further characterization of the segments: intake, liking and eating rate

Segments in intake were related to liking and eating rate through mixed model ANOVA where the segments were included as a fixed factor in the model.

The segments did not differ with respect to overall liking or eating rate but had different responses to granola particle size (p<0.01 for liking and p<0-001 for eating rate). Both "small rejectors" and "small eaters" showed a decrease in liking for yogurt with small granola (Figure 7). For the small eaters, the eating rate for these yogurts was higher compared to other products. The small rejectors on the other hand had the largest drop in liking for small granola, but only small differences in eating rate. The thick-sensitive group presented smaller differences in liking, although small granola was the least liked product for this segment as well. This group had higher eating rates for the small granola when it was combined with thick yogurt.

Insert figure 7 around here

3.3.3. Temporal drivers and preventers of intake per segment

Although flavour attributes also varied with the textural changes in the samples, and were relevant for the dynamics of perception, they are expected to be less relevant than textural attributes as determinant of the changes in intake. As shown in previous studies, texture, not flavor, determines expectations of satiation – as studied in dairy products (Hogenkamp et al, 2011). Thus, the focus of this part of the discussion will be the effect of dynamic changes in texture perception and their effect in eating behavior and affective responses. The dynamic sensory attributes as measured by TCATA were divided into three stages during the oral processing (beginning, middle, end), and related to the average intake, liking and eating rate for each of the segments, to better understand the temporal drivers of each of these perceptions in the three groups of consumers. Figure 8 highlights the temporal drivers of intake, liking and eating rate for the three consumer segments.

For segment S1 "small eaters", sandiness, as imparted by small particles, was the most important driver of the increase in eating rate and also of intake throughout the entire oral processing period (beginning, middle, end); fullness (thick samples) was also partially correlated to intake throughout the eating period (beginning, middle, end). Dynamic textural attributes related to large particles acted as preventers of intake at different stages in the oral processing period: hardness was relevant in the beginning and middle of the eating period, gumminess in the end, while coarseness was highlighted a preventer throughout (beginning, middle, end). For "small eaters", drivers of intake were inversely correlated to liking, which was mostly driven by dynamic attributes characterizing samples with large particles (hard, coarse and gummy at different stages in the oral processing).

For the second segment S2 "thick sensitive" consumers, it is very interesting to see how liking, intake and eating rate pointed to different directions in the temporal perceptual space. Dynamic attributes related to the easily in-mouth managed sample properties were the most important drivers linked to eating rate increase: airiness and sandiness positively correlated to an increase of eating rate. Fullness of thicker samples (b, m, e) and hardness/coarseness (larger particles) negatively correlated to eating rate throughout all the eating period. However, intake was driven by gumminess (larger particles) particularly at the beginning of the eating period. Coarseness and hardness were linked to an increased liking for this segment. These last points may explain the "thick sensitivity": while fullness was a preventer of eating, the presence of large particles imparting coarseness and hardness may have counteracted the effect of the fullness in thick-large samples, while sandiness together with fullness may have acted as a preventor of intake (thick-small samples).

With respect to segment S3 "small rejectors", sandiness, as imparted by small particles, was the main preventer of intake throughout all the mastication period highly correlated to (dis)liking, while hard, coarse and gummy (larger particles) acted as drivers of consumption, highly correlated to liking. It is interesting to observe, how eating rate in this segment (driven by thin/thick properties) is not correlated to intake (90 degree angle).

Insert figure 8 around here

4. DISCUSSION

4.1. Why do consumers eat less of small granola? And the effects of liking and eating rate.

At the population level, small granola particles were consumed at a faster eating rate for both thin and thick yogurt matrices. Additionally, small granola particles required less chews per spoonful and were kept for shorter periods in the mouth in comparison to medium and large particles (data not shown). It was expected that yogurts with small granola would be consumed in higher quantities as previous literature has reported a higher intake for products requiring less oral processing efforts (Bolhuis et al., 2014; Ferriday et al., 2016; Lasschuijt et al., 2017; McCrickerd et al., 2017). In this study, results showed the opposite effect, on average, intake was lower for the small granola in the overall population, and there could be different reasons for this. Viscosity (measured instrumentally; data not shown) increased considerably with the addition of small granola particles, as compared to larger particles for the same type of yogurt (thin or thick). Increases in viscosity were shown to decrease intake of semi-solid foods (de Wijk et al., 2008; Zijlstra et al., 2009); so, it could be that the lower intake observed in this study was more related to the increased viscosity rather than to the smaller particles when it comes to oral processing, especially in thick yogurts with small particles. Increased viscosity was also observed with the time of contact between yogurt and small granola, so there could have been an increase in viscosity throughout the eating period, from the start to the end of the session, and this could have been different among samples (higher increases for the smaller particle sizes). Previous studies have also highlighted that both viscosity and solid food particles are modulators of satiety expectations (Hogenkamp and Schiöth, 2013, Hogenkamp et al., 2011, Marcano et al., 2015). However, results in the present paper point in another direction as main reasons behind this effect. Liking, and the interaction of liking with oral processing effects on eating rates, may have influenced intake; on average, intake was higher for the more liked products. These results are in line with results of previous experiments on the same category of samples (yogurts with cereals) when path modelling was used, in which liking also imparted positively on portion-size selection, more strongly than satiety expectation cues (Nguyen et al., 2020). That liking is a driver of consumption is not new, it has been studied in the past for other types of samples, highlighting the effect of liking on satiation (see for example De Graaf et al., 1999, Yeomans, 1996). Nguyen et al. (2020) suggested that individual differences could underly the perception of satiety, satiation and portion size selection, based on differences in oral processing styles by different consumers. What is novel in the present study is the understanding of how liking, and the effects on eating rate by changes in the oral processing by texture modifications, could differently affect consumers with distinct eating behaviors.

4.2. The differentiated effects of oral processing on liking and intake in consumers with different eating patterns

Segmentation of consumers based on their intake patterns (intake mapping) highlighted distinct relations between liking, eating rate and food intake in different subjects. For example, when one looks at the eating rate by segments, segment 1 “small eaters” was more sensitive to the changes in texture (significantly enhanced by the small particles), this effect was only shown for the thin samples in segment 2, and no great changes in eating rate were shown for the “small rejectors” (Figure 7b). Similarly, segment 3 “small rejectors” was more strongly affected in their liking for the small particles than the other segments (Figure 7a). A growing body of research is pointing at the importance of dynamic sensory perception in creating expectations of satiation and portion size selection (Morell et al., 2014; Marcano et al., 2015; Tarrega et al., 2016; Nguyen et al., 2017). The present paper goes also further in this issue, showing how individual differences also underlie how important different dynamic perceptions are for consumers with different intake patterns. Temporal sensory drivers per segment (Figure 8) showed different effects of the textural modifications on the three groups, both for liking and intake; what could be a driver of intake for some, it could act as preventer for others. Nguyen et al. (2020) suggested that individual differences underlying satiation expectations and portion size selection could be linked to preferred eating styles of consumers (as defined by Jeltema et al. 2016). Unpublished work by the same authors (in prep) shows that consumers with different eating styles may have different drivers of liking, different drivers of satiation expectations and that some consumers may give more importance to particle-size rather than viscosity for assessing satiety or choosing portion size. Engelen and van der Bilt (2008) proposed that intra-individual differences in texture perception could be explained by variations in oral physiology (oral processes, oral sensitivity and receptors), while tongue movements, temperature and saliva composition are also of importance for texture perception of semisolids, and widely vary across individuals. In a recent paper, Puleo et al. (2019) found groups of consumers having different sensitivity to graininess and that those differences affected liking patterns in the groups; they highlighted that texture sensitivity knowledge would be useful for the food industry to develop tailored foods. Other parameters like culture or food exposure could also influence texture perception, but the subjects in the present study were quite homogeneous in that respect. Different patterns in intake and liking may be related to specific eating styles or restrained eaters as shown here.

Undoubtedly, there are many questions still to be answered, if it is the eating style or other reasons like differences in sensitivity underlying the effects of oral processing on liking and food intake, is still to be unveiled, and should be tackled in future studies

5. CONCLUSIONS

This study shows that individual differences underly how texture perception influence eating behaviour, food intake and liking. Consumers may use different oral processing strategies to manipulate foods, or have differentiated textural sensitivities, influencing preferred textures and their intake. It is also possible that different groups of consumers may give different importance to textural attributes when deciding their prospective portion size, thus having different intakes. Dynamic perception is key to understand these relations. A body of published research indicates it is possible to reformulate foods texture to influence satiety expectations, eating rate, portion size selection and ultimately intake, aiming at targeting overeating; however, individual differences need to be better understood to know the implications for different groups of consumers. In a world where food personalization is increasing in focus, future research needs to unveil and characterize those individual differences from the consumer point of view, on different product categories, and how those are related to dynamic sensory properties, food structure and formulation.

REFERENCES

Bolhuis, D. P., Forde, C. G., Cheng, Y., Xu, H., Martin, N., & de Graaf, C. (2014). Slow food: Sustained impact of harder foods on the reduction in energy intake over the course of the day. PLoS One, 9(4), e93370. https://doi: 10.1371/journal.pone.0093370.

Castura, J. C., Antúnez, L., Giménez, A., & Ares, G. (2016). Temporal check-all-that-apply (TCATA): A novel dynamic method for characterizing products. Food Quality and Preference, 47(Part A), 79–90.

Castura, J. C. (2018). tempR: Temporal Sensory Data Analysis. R package version 0.9.9.15. http://www.cran.r-project.org/package=tempR/

De Graaf, C. De Jong, L.S. Lambers A.C. (1999) Palatability affects satiation but not satiety. Physiology & Behavior, 66 (4) (1999), pp. 681-688

De Wijk, R.A., Zijlstra, N., Mars, M., de Graaf, C., & Prinz, J.F. (2008). The effects of food viscosity on bite size, bite effort and food intake. Physiology and Behavior, 95: 527-532.

den Uijl, L.C., Jager, G., de Graaf, C., Waddell, J., & Kremer, S. (2014). It is not just a meal, it is an emotional experience – A segmentation of older persons based on the emotions that they associate with mealtimes Appetite, 83: 287-296.

Endrizzi, I., Gasperi, F., Rodbotten, M., & Naes, T. (2014). Interpretation, validation and segmentation of preference mapping models. Food Quality and Preference, 32, 198-209. doi:10.1016/j.foodqual.2013.10.002

Engelen, L., & Van Der Bilt, A. (2008). Oral physiology and texture perception of semisolids. Journal of Texture Studies, 39(1), 83-113.

Ferriday, D., Bosworth, M., Godinot, N., Martin, N., Forde, C. G., van Den Heuvel, E., Appleton, S., Mercer Moss, F., Rogers, P. J., & Brunstrom, J. M. (2016). Variation in the oral processing of everyday meals is associated with fullness and meal size; a potential nudge to reduce energy intake? Nutrients, 8(5), e315. https://doi: 10.3390/nu8050315

Forde, C. G., van Kuijk, N., Thaler, T., de Graaf, C., & Martin, N. (2013a). Oral processing characteristics of solid savoury meal components, and relationship with food composition, sensory attributes and expected satiation. Appetite, 60(1), 208–219. https://doi: 10.1016/j.appet.2012.09.015.

Hogenkamp, P. S., Stafleu, A., Mars, M., Brunstrom, J. M., & de Graaf, C. (2011). Texture, not flavor, determines expected satiation of dairy products. Appetite, 57(3), 635–641.

Hogenkamp, P.S. & Schiöth H.B. (2013) Effect of oral processing behaviour on food intake and satiety

Trends in Food Science & Technology, 34 (1), pp. 67-75

Jeltema, M., Beckley, J. and Vahalik, J. (2016) Food texture assessment and preference based on Mouth Behavior. Food Quality and Preference, 52, pp. 160-171

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. Journal of Statistical Software, 82(13), 26.

Lasschuijt, M. P., Mars, M., Stieger, M., Miquel-Kergoat, S., de Graaf, C., & Smeets, P. A. M. (2017). Comparison of oro-sensory exposure duration and intensity manipulations on satiation. Physiology & Behavior, 176, 76-83.

Lawless, H. T., & Heymann, H. (2010c). Sensory evaluation of food: Principles and practices. New York: Springer.

Le, S., Josse, J., Husson F(2008). FactoMineR: An R Package for Multivariate Analysis. Journal of Statistical Software, 25(1), 1-18. 10.18637/jss.v025.i01

Lenth, R. (2019). emmeans: Estimated Marginal Means, aka Least-Squares Means. R package version 1.4.2.

Marcano J., Morales D., Vélez-Ruiz, J.F., Fiszman S (2015). Does food complexity have a role in eliciting expectations of satiating capacity? Food Research International, 75, pp. 225-232

McCrickerd, K, Lim, CMH, Leong, C, Chia, EM, Forde, CG (2017). Texture-Based Differences in Eating Rate Reduce the Impact of Increased Energy Density and Large Portions on Meal Size in Adults. The Journal of Nutrition, Volume 147, Issue 6, Pages 1208–1217, https://doi.org/10.3945/jn.116.244251.

McEwan, J. A. (1996). Preference mapping for product optimization. In, Multivariate analysis of data in sensory science: Elsevier.

Morell, P., Fiszman, S. M., Varela, P., & Hernando, I. (2014). Hydrocolloids for enhancing satiety: Relating oral digestion to rheology, structure and sensory perception. Food Hydrocolloids, 41, 343–353.

Mosca, A.C., Pohlenz Torres, A., Slob, E., McEwan, J.A., de Graaf, K., Stieger, M. (2019). Small food texture modifications can be used to change oral processing behaviour and to control ad libitum food intake. Appetite, 142, 104375.

Nguyen, Q. C., Wahlgren, M. B., Almli, V. L., & Varela, P. (2017). Understanding the role of dynamic texture perception in consumers' expectations of satiety and satiation. A case study on barley bread. Food quality and preference, 62, 218-226. https://doi.org/10.1016/j.foodqual.2017.06.006

Nguyen, Q.C., Næs,T., & Varela, P. (2018). When the choice of the temporal method does make a difference: TCATA, TDS and TDS by modality for characterizing semi-solid foods. Food Quality and Preference, 66: 95-106.

Nguyen, Q. C., Næs, T., Almøy, T., & Varela, P. (2020). Portion size selection as related to product and consumer characteristics studied by PLS path modelling. Food Quality and Preference, 79, 103613.

Puleo, S., Miele, N. A., Cavella, S., Masi, P., & Di Monaco, R. (2019). How sensory sensitivity to graininess could be measured? J Texture Stud.

Robert, P., & Escoufier, Y. (1976). A unifying tool for linear multivariate statistical methods: the RV-coefficient. Journal of the Royal Statistical Society. Series C (Applied Statistics), 25(3), 257-265. doi:10.2307/2347233

Tarrega, A., Marcano, J., & Fiszman, S. (2016). Yoghurt viscosity and fruit pieces affect satiating capacity expectations. Food Research International, 89, 574-581.

Wickham H. (2016) ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Yeomans, MR (1996) Palatability and the micro-structure of feeding in humans: The appetizer effect Appetite, 27 (2) pp. 119-133

Zijlstra, N., de Wijk, R., Mars, M., Stafleu, A., & de Graaf, C. (2009). Effect of bite size and oral processing time of a semisolid food on satiation. The American journal of clinical nutrition, 90(2), 269-275.

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Tables

Table 1: p-values from model 2 for each of the responses

Effect	Intake	Liking	Eating rate
Viscosity (2 levels)	<0.001	0.043	<0.001
Granola (3 levels)	<0.001	<0.001	0.002
Viscosity*Granola	<0.001	0.046	<0.001
Gender	<0.001	0.501	<0.001
Viscosity*Gender	0.110	0.911	0.648
Granola*Gender	0.084	0.739	0.578

Figure captions

Figure 1- QDA perceptual space as highlighted by PCA

Figure 2: Temporal profiles for the six yogurts by attribute

Figure 3: Estimates of product effect for liking, intake (amount eaten in grams), and eating rate. Bars are calculated as the Least Square Means +/- one standard error.

Figure 4: PCA consumer loadings for intake colored according to the correlation with liking. Each dot represents the loading for one consumer (intake data), and the color and size represent the correlation with the liking data. Red indicate negative correlations, blue positive correlation. Larger dots indicate larger squared correlations.

Figure 5: (a) Consumer loadings from intake (amount eaten in grams) with the three segments highlighted by different colors. (b) LSmeans for product effects on intake per segment (averaged over gender) Segment 1 (blue): Small eaters. Segment 2 (green): Thick sensitive. Segment 3 (red): Small rejectors. Bars are calculated as the Least Square Means +/- one standard error.

Figure 6: Intake Mapping. Sensory loadings from sensory description via QDA and loadings for intake (I), liking (L) and eating rate (ER) for the identified consumer segments.

Figure 7: Characterization of the three segments, (a) Liking; (b) Eating rate. Bars are calculated as the Least Square Means +/- one standard error.

Figure 8: Temporal drivers of liking and intake. Representation of the dynamic sensory attributes (TCATA) across all oral processing intervals via MFA; beginning (b), middle (m) and end (e). Liking (L), intake (I) and eating rate (ER) for the three segments were plotted as supplementary variables.