Norwegian University of Life Sciences
Faculty of Chemistry, Biotechnology and Food Science

Philosophiae Doctor (PhD)
Thesis 2019:5

Better understanding of the relation of the dynamic sensory perception of solid and semi solid foods with consumers' preferences and their perception of satiety

Forbedret innsikt om relasjonen mellom dynamisk sensorisk oppfattelse og forbrukernes preferanser og metthetsfølelse, med fokus på faste og delvis flytende matvarer

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Abstract

Nowadays, overweight and obesity has been recognized as one of the main reasons that leads to many non-communicable diseases such as diabetes, high blood pressure, cardiovascular disease and in some cases cancer. Therefore, it is necessary to reduce or at least control overweight and obesity. Some potential solutions have been proposed but they have not been very successful due to the complexity and multi-dimensionality of overweight and obesity. In this context, changing food intake or portion size selection has been proposed as a potential effective solution. However, when changing the meal size, one often changes or replaces food ingredients, which in turn, may change consumer satisfaction. Therefore, the main challenge is to get a balance between controlling meal size and satisfying consumer expectations. To deal with this challenge, a holistic approach is required integrating both product (i.e. sensory attributes) and consumer (i.e. expectations, characteristics) perspectives.

Previous research has found that the perception of texture is closely related to satiety expectations and potentially, portion size selection. Sensory attributes are dynamic perceptions that change from one moment to another moment during mastication, and dynamic perception has been hypothesized to influence satiety perception. Thus, temporal descriptive methods are recommended to capture these perceptions. Different temporal methods may have both advantages and limitations. For that reason, the first part of the thesis focuses on method comparisons with the purpose of pointing out the most appropriate method to better understand dynamic perception and satiety related expectations. Using food products with identical composition but varying in texture, the results indicate that TCATA is more suitable for descriptive purposes, whereas TDS could be better suited if the concern is the dominant attribute.

Solid and semisolid food products (barley bread, yoghurt) were characterized by both static and dynamic sensory attributes. These attributes were used to identify the drivers of consumer expectations (i.e. liking, satiation, satiety). From that, flavour was found as the main attribute driving liking, whereas texture was deemed essential for driving the expectations of satiation and satiety.

The next focus in the thesis was to investigate the relations between consumer expectations and prospective portion size, in an integrated approach. In this framework,

exploratory blocks (i.e. liking, satiation, satiety) influence each other and together predict the response block (i.e. portion size selection). A path modelling approach is a valuable tool that estimates these relations and highlights blocks or variables which are important in a prediction model. In this part of the thesis, both standard PLS-PM and SO-PLS-PM, which deal with multi-dimensionality in blocks, were used. The results demonstrated that liking was a key determinant of portion size selection. In addition, satiety was predicted by satiation. These results were observed in two data sets (yoghurt, biscuit) with different complexities of sensory properties. Added to this, different groups of consumers showed different drivers for portion selection, highlighting the importance of the study of individual differences in satiety perception.

In conclusion, this thesis provided three main findings: (1) temporal descriptive methods are recommended to describe sensory perception particularly when relating them to oral processing, and the methods are selected depending on the specific purpose of each research; (2) consumer satiety expectations, and their relation to liking and portion size selection are driven by different sensory modalities and subjected to individual differences; and (3) the relations between consumer expectations can be effectively modelled and interpreted using SO-PLS-PM. These results are important at industrial level for developing satiety-related food products and from a methodological point of view, in research applications.

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List of abbreviations

CA	Correspondence Analysis
CATA	Check All That Apply
ConCA	Escofier's Conditional CA
CVA	Canonical Variate Analysis
DATI	Dual Attribute Time Intensity
JBMB®	Jeltema/Beckley Mouth Behavior
LV(s)	Latent variable(s)
M-TDS	Temporal Dominance of Sensations by modalities
MANOVA	Multivariate Analysis of Variance
MB	Mouth behavior
MFA	Multiple Factor Analysis
MV(s)	Manifest variable(s)
Path-ComDim	Path Common Dimensions
PC(s)	Principal component(s)
PCA	Principal Component Analysis
PCP	Principal Components of Predictions
PLS	Partial Least Squares
PLS-PM	Partial Least Squares path modelling
QDA®	Quantitative Descriptive Analysis®
SO-PLS	Sequential Orthogonalised Partial Least Squares
SO-PLS-PM	Sequential Orthogonalised Partial Least Squares path modelling
SVD	Singular Value Decomposition
GSVD	Generalized Singular Value Decomposition
TCATA	Temporal Check All That Apply
TDS	Temporal Dominance of Sensations
TI	Time Intensity

List of papers

1. 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.
2. 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.
3. Nguyen, Q. C., Næs, T., Almøy, T., & Varela, P. (2018). Portion size selection as related to product and consumer characteristics studied by PLS Path Modelling. *Food Quality and Preference, (In Press)*.
4. Nguyen, Q. C., Liland, K. H., Tomic, O., Tarrega, A., Varela, P., Næs, T. SO-PLS path modelling as holistic approach to explore relations between consumer liking, expectations of satiety and portion size selection. (*Manuscript*).

Introduction

According to the World Health Organization (WHO), 39% of adults aged 18 years and over (39% of men and 40% of women) were overweight, and about 13% of the world's adult population (11% of men and 15% of women) were obese in 2016. The worldwide prevalence of obesity nearly tripled between 1975 and 2016 ("Obesity and overweight", 2018). Obesity has become an international public health issue that affects the quality of life, increases the risk of illness, and raises health-care costs in countries in all parts of the world (Bray, Frühbeck, Ryan, & Wilding, 2016).

It is worth noting that obesity is a complex and multifactorial phenomenon resulting from genetic, epigenetic, physiological, behavioural, sociocultural, and environmental factors (Janesick, Shioda, & Blumberg, 2014; Keith et al., 2006). Thus, little progress for preventing obesity has been made and effective preventive measurements often fail (Kleinert & Horton, 2015). The treatment of obesity is a comprehensive intervention, including implementation of three strategies: lifestyle or behavioural training, dietary change to reduce energy intake, and an increase in physical activity (The Look AHEAD Research Group, 2014). For the first strategy, a systematic review (Ryan & Heaner, 2014) of evidence showed that these programs provide on average a weight loss of about 3% per year, but long-term compliance is generally poor. Similarly, for the third strategy, although physical activity is effective in the short term in controlled settings, the activities and their benefits are not always sustained (The Look AHEAD Research Group, 2014). The second strategy (i.e. diets for weight loss) may have good potential (Bray et al., 2016).

More specifically, to control meal size and tackle overeating, there is a need to formulate healthy and satiating low-energy foods reaching consumers' acceptance (Murray & Vickers, 2009). Multiple variables influence the onset of satiation and satiety; therefore, designing foods that provide early satiation and enduring satiety require the consideration of overlapping interactions among food composition, food structure, oral processing, and dynamic sensory perception as well as psychological inputs such as environment and hedonic liking (Campbell, Wagoner, & Foegeding, 2017). This interaction is displayed in Figure 1.

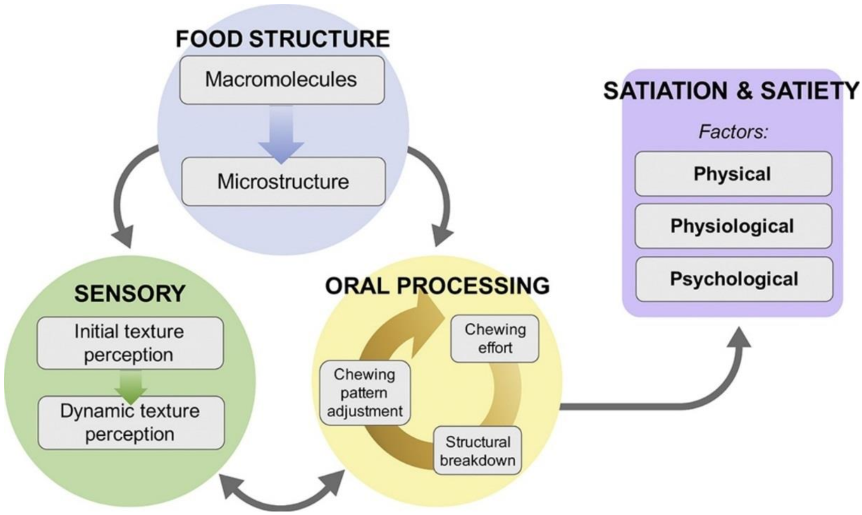

Figure 1. The interaction of food structure, sensory and oral processing in designing satiety food (Campbell et al., 2017).

Until now, many studies of meal size have indicated that when deciding on a particular portion size, our strategy may be guided by a concern to ensure that a portion of food will deliver adequate satiety (Brunstrom & Shakeshaft, 2009). Satiety-related perception consists of two concepts: satiation and satiety. Particularly, satiation occurs during eating, involving the processes by which food intake is terminated, while satiety occurs after eating, inhibiting further eating until the return of hunger (Bellisle, Drewnowski, Anderson, Westerterp-Plantenga, & Martin, 2012).

Considering the effect of energy density of a meal on postprandial satiety, it has been known that satiety is not affected by the energy of food intake (Carbonnel, Lémann, Rambaud, Mundler, & Jian, 1994), and thus consumers often use the prior experience to moderate their intake (Brunstrom, 2011). In general, the focus is to decide the amount eaten or food intake governed by using the associations between sensory attributes and their metabolic consequences or expectations before consumption (Brunstrom & Rogers, 2009; Brunstrom, Shakeshaft, & Scott-Samuel, 2008).

People are in fact very good at estimating satiety-related expectations (Brunstrom, 2014; McCrickerd & Forde, 2016; Wilkinson & Brunstrom, 2009). So, when trying to link product characteristics to their satiating properties, it is possible to measure consumers' expectations instead of actual food intake. These expectations are not straightforward measures, they are based on the complex interaction of various parameters like energy content, volume, weight, sensory properties, oral process, etc. (de Graaf, 2011; Forde, van Kuijk, Thaler, de Graaf, & Martin, 2013). Therefore, a holistic approach including all these parameters could be a good way for better understanding the relations between consumer expectations.

Regardless of actual or expected measures, sensory profile of the product is the first major step to link product characteristics and their effects. Traditionally, sensory perception has been described by static methods with trained assessors (e.g., QDA®) or consumers (e.g., CATA). Nevertheless, it becomes necessary to describe the sensory attributes as dynamic perceptions. This is due to the dynamics of sensory perceptions which change from the first bite to the swallowing point in response to different stages of the mastication (Morell, Fiszman, Varela, & Hernando, 2014). The dynamics of the oral processing process can be summarized in Figure 2.

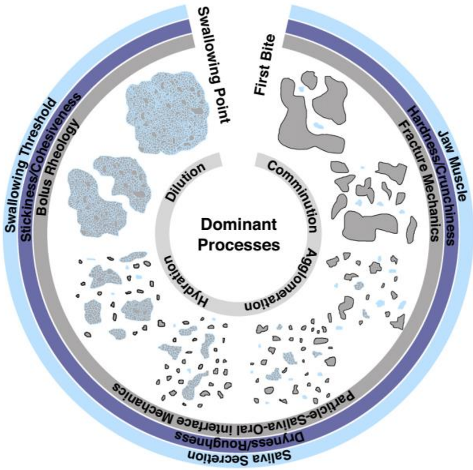

Figure 2. A schematic of the oral processing of a solid food (Witt & Stokes, 2015).

In this schematic, oral processing can be described from a time perspective by the changes to the (inner-ring) food physics; (middle-ring) sensorial; and (outer-ring) oral physiological properties (Witt & Stokes, 2015).

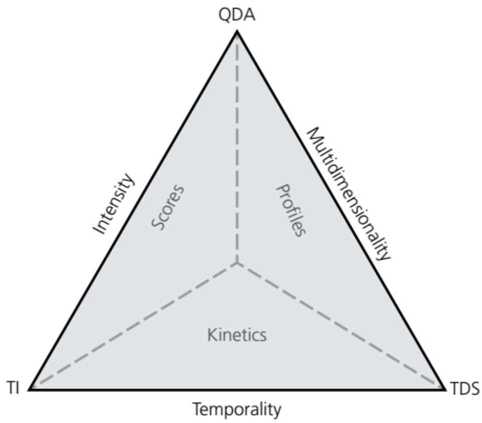

Figure 3. Conceptual differences between QDA®, TI and TDS (Schlich, 2017).

For that reason, temporal methods come up as appropriate tools to describe sensory attributes of food products. To understand perceptions during oral processing, several methods have been applied, each method describes different kinds of information. Figure 3 illustrates how different descriptive approaches (QDA, TI and TDS) are related to each other and which information is described in each approach. Recently, TCATA (Castura, Antúnez, Giménez, & Ares, 2016), an extension of CATA method, has been proposed to capture dynamic perceptions in which assessors are able to select some applicable attributes at a given time. Although some studies have indicated that TCATA is better than other temporal methods in product characterization, the result is still debated in some points such as the concept of dominance in TDS (Varela et al., 2017), the ease/difficulty of the selecting and unselecting task in TCATA (Ares et al., 2016; Ares et al., 2015).

Hypotheses and Objectives

Hypotheses

H_1: Dynamic sensory perception during oral processing influences expectations of satiety and satiation.

H_2: Consumer liking, expectations of satiation and satiety are driven by different sensory perceptions.

H_3: Liking, satiation and satiety expectations differently influence portion size selection.

Objectives

The main objective of the thesis is to get a better understanding of the relation of the dynamic sensory perception of solid and semi solid foods with consumer expectations of satiety. The thesis focuses on the interface of sensory and consumer science and sensometrics disciplines with three specific objectives as follows:

1. Applying, comparing and optimizing temporal methods to capture the dynamics of sensory perception as linked to consumers' expectations

Different temporal methods (TDS, TCATA and some proposed variants of these methods) were compared with the purpose of pointing out the advantages and limitations of these methods. With the findings from this part, it was possible to make methodological recommendations for researchers being able to choose the appropriate methods which meet the goal of the research questions, and to select the most appropriate method for the next steps in the thesis research

2. Relating product sensory attributes to liking, satiety and finding the drivers for these expectations

The focus was to better understand the consumer expectations of liking and satiety from a sensory perspective. Consumer tests were designed to collect information about liking and expectations of satiety. This information paired with product sensory data (static and dynamic) was modelled to identify the main drivers of liking and satiety and how these expectations interact to form consumers' assessment.

3. Assessing the pros and cons of different approaches in building the model for predicting a portion size selection from other aspects of consumers' expectations

Consumers' expectations did not only depend on sensory attributes but also could be driven by non-sensory characteristics, consumer characteristics, and more important, hedonic and satiety-related expectations interacting with each other. Therefore, an integrated framework where various aspects such as liking, satiety, hunger and fullness feelings, attitudes to healthfulness of foods were modelled together to enable the further explanations of portion selection. The prediction model should be a good tool to shed light on the relations between consumers' expectations and the effects of consumers' attitudes on these expectations.

PLS-PM was used to estimate both direct and indirect effects between consumer characteristics and consumer expectations. In two case studies, this approach presented some limitations, especially when taking the multi-dimensionality of sensory and consumer data into account. Some potential approaches (e.g., SO-PLS-PM) had been proposed to overtake the issue. In addition, pros and cons of each model were discussed.

Theoretical background

Oral processing and its role in sensory perception

Texture perception

Food oral processing is an essential step in the eating process, which aims at preparing the food for swallowing and digestion. It is not only important for the ingestion and digestion, but also plays a key role in the sensory perceptions (Foster et al., 2011) and the palatability of foods (Jourdren et al., 2016).

During oral processing, structure of food is broken down with force applied by teeth and/or tongue (mechanical breakdown) and lubricated (possibly hydrated or dissolved) with saliva until the time that a swallowing threshold is reached (Pascua, Koç, & Foegeding, 2013). A mouth process model was proposed by (Hutchings & Lillford, 1988) with three dimensions: the rheological behavior of food (Degree of structure), the saliva participation (Degree of lubrication) and the sequences (Time) shown in Figure 4.

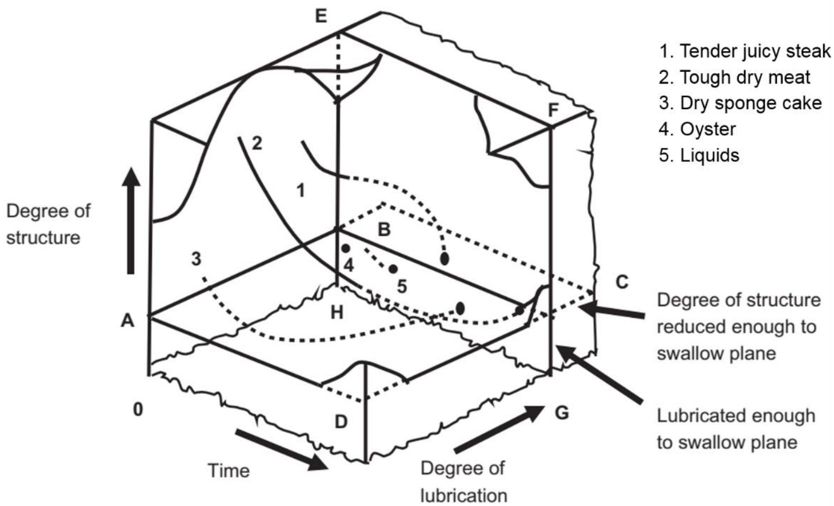

Figure 4. The mouth process model (Hutchings & Lillford, 1988).

More specifically, the oral processing can be split into the following six stages: (1) first bite, (2) comminution, (3) granulation, (4) bolus formation, (5) swallow and (6) residue (Foster et al., 2011; Stokes, Boehm, & Baier, 2013). These stages are depicted in Figure 5.

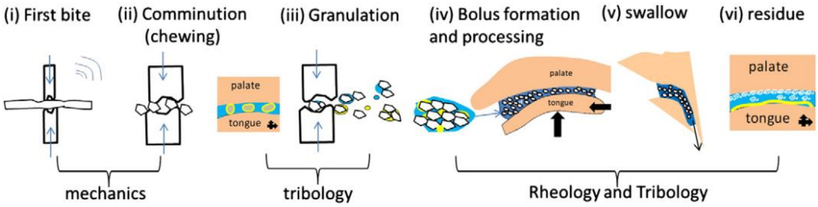

Figure 5. Stages during oral processing of solid food (Stokes et al., 2013).

In this process, at early stage when the ingested food is still large size and in bulk, breaking and large deformation dominates, and sensation of food texture will be mostly of those related to rheological or mechanical properties of the food. With the decrease of food particle size and/or thinning down of fluid food (with the help of saliva) at a later stage of oral processing, rheology properties become less relevant but surface friction and lubrication (i.e. tribology properties) becomes a dominating mechanism for texture perception. The rheology-tribology transition is very importance because sensory properties are perceived with respect to the dominating mechanisms of oral sensation (Chen & Stokes, 2012).

Flavour perception

Flavor perception during food consumption is determined by the nature and amount of volatile and nonvolatile compounds, the availability of these compounds to the sensory system as a function of time, depending on the breakdown of the food matrix through mastication (Overbosch, Afterof, & Haring, 1991). The process of mastication involves flavour release can be explained through several hypotheses: matrix–aroma or taste interactions (Boland, Buhr, Giannouli, & van Ruth, 2004), oral behavior (Mestres, Moran, Jordan, & Buettner, 2005; Saint-Eve et al., 2006), and sensory interactions (Bult, de Wijk, & Hummel, 2007). More specifically, flavour release rate is more affected by the frequency of oral movements, and then by in-mouth food manipulations, than by subject efficiency in breaking down the food sample (Tarrega, Yven, Sémon, & Salles, 2011). Some studies indicate that overall flavour intensity increased with an increase in mastication rate (Mestres, Kieffer, & Buettner, 2006), the complexity of movements of tongue (Baek, Linforth, Blake, & Taylor, 1999; de Wijk, Engelen, & Prinz, 2003);

conversely, reduced with an increase in viscosity (Foster et al., 2011) and firmness of foods (Saint-Eve et al., 2011).

Bolus information and criteria of swallowing

The primary role of mastication is to transform a mouthful of food into a bolus ready for swallowing (Prinz & Lucas, 1995). This is achieved by reducing the food to small particles and by lubricating it with saliva and any liquid released from the food itself (Peyron, Mishellany, & Woda, 2004). During the process, texture is one of the decisive factors to obtain the swallowing threshold through the effect of particle size distribution in bolus, lubrication by saliva and bolus wetting (Gavião, Engelen, & Van Der Bilt, 2004; Peyron et al., 2004). The swallowing threshold comprises many parameters (Peyron et al., 2011) and the understanding of physical mechanisms underlying the swallowing is not completely clear (Loret et al., 2011). Many authors, however, agree that the food bolus should be viscous, plastic, and cohesive to be safely swallowed (Amemiya, Hisano, Ishida, & Soma, 2002; Coster & Schwarz, 1987; Nicosia & Robbins, 2001; Prinz & Lucas, 1997), emphasizing the important role of food texture in determining swallowing threshold.

Individual differences in oral processing

Oral processing is both a physical process modulated by mechanical and geometrical properties of the food, and a physiological process controlled by central nerve system (Woda, Mishellany, & Peyron, 2006). Thus, bolus properties at the end of mastication depend on both food and subject characteristics, as well as on the oral strategy of the subject eating this specific food product (Panouillé, Saint-Eve, Déléris, Le Bleis, & Souchon, 2014; Yven et al., 2012). In fact, the subjects change the chewing activity according to sample textures (Tarrega, Yven, Sémon, & Salles, 2008). Evidently, the physiological characteristics of subjects play an important role in the oral processing (Chen, 2014).

When considering individual differences, it can be assumed that subjects have different strategies, but they all aim at producing a bolus suitable for swallowing (Mishellany, Woda, Labas, & Peyron, 2006). Jeltema and colleagues (Jeltema, Beckley, & Vahalik, 2015; Jeltema, Beckley, & Vahalik, 2014) developed a tool, namely JBMB®, to classify individuals into four major groups of MB: *chewer*, *cruncher*, *smoosher* and *sucker* in response to the way how they manipulate food products in their mouths. In practice, consumers are asked to select the image that “best describes you, most like you”. These images are shown in Figure 6. In principle, *cruncher* and *chewer* would be those who like to use their teeth to break down foods, whereas *sucker* and *smoosher* preferred to manipulate food between the tongue and roof of the mouth.

Figure 6. Graphic MB typing tool (Jeltema et al., 2015).

Individuals use different mechanisms for the oral breakdown of food so that at any point, different groups of individuals would experience the samples differently (Brown & Braxton, 2000). In other words, the perceived intensity of the sensory attributes change from moment to moment; thus, it requires dynamic descriptive methods to capture the dynamic nature of food sensations (Lawless & Heymann, 2010c). Additionally, consumers have preferred ways to manipulate and manage food in the 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). For that reasons, sensory perceptions should be considered as time-dependent instead of static events.

Dynamic rather than static sensory perception

Introduction of temporal methods

Processes involved in eating, e.g., mastication and salivation, are recognized as dynamic processes (Dijksterhuis & Piggott, 2000). Some models have been proposed to explain the breakdown pathway of food during oral processing that emphasized the dynamic and complex nature of sensory perceptions during the continuous transformation of food from first bite to swallowing (Hutchings & Lillford, 1988; Koc, Vinyard, Essick, & Foegeding, 2013). Capturing temporal sensory changes has long been an objective of researchers seeking to obtain a more complete understanding of how food products are perceived (Cliff & Heymann, 1993; Holway & Hurvich, 1937; Jellinek, 1964). However, traditionally, sensory methods (e.g., QDA®) have focused on static judgements, measuring the averaged intensities of sensations instead of the temporal dimensions (Di Monaco, Su, Masi, & Cavella, 2014). These methods do not consider the temporal aspects of sensory perception and may miss crucial information for understanding consumer preferences (Lawless & Heymann, 2010c).

Various temporal sensory methods have been developed for dynamic sensory characterization (Cadena, Vidal, Ares, & Varela, 2014). TI, used quite extensively since 1970s (Lee & Pangborn, 1986), allows assessors to indicate the perceived intensity of one sensory attribute over time. DATI (Duizer, Bloom, & Findlay, 1997), the extension of TI, is used as a method to collect the perceptions of two attributes simultaneously.

TDS is a relatively recent method in sensory analysis that gives the opportunity to describe the evolution of the dominant sensory attributes during tasting of a food or beverage product. Ep Köster, at the Centre Européen des Sciences du Goût (CESG) in Dijon, France, initiated TDS in 1999. The first visualisation and analysis of TDS data were presented at the Pangborn Sensory Science Symposium in Boston (Pineau, Cordelle, & Schlich, 2003). TDS is well established in the sensory domain now and has been applied to many product categories. The applications of TDS are recently reviewed by Di Monaco and colleagues (Di Monaco et al., 2014). This method consists in presenting to the assessors a list of attributes, assessors are then asked to assess which of the attributes is perceived as dominant. During the course of the evaluation, when the assessor considers that the dominant attribute has changed, he or she has to select the new dominant sensation (Labbe, Schlich, Pineau, Gilbert, & Martin, 2009; Pineau et al., 2009). It is important to bear in mind that only one dominant attribute can be selected at a given time. Owed to this, the concept of "dominance" has been argued. Controversial issues highlighted were around how attributes are selected, the drivers of transitions between attributes, the competition of sensory modalities and how some phenomena like dumping or dithering could happen at some stages in TDS (Varela et al., 2017).

TCATA, the temporal extension of CATA developed in recent years, could potentially overcome some of those issues. TCATA enables the evaluation of more than one attribute at each time, resulting in a more detailed description of sensory characteristics of products over time (Ares et al., 2015; Castura, Antúnez, et al., 2016). Other solution to the drawback of TDS is to implement TDS in separate steps; that is, assessors are asked to perform TDS for one sensory modality (e.g., flavour) and then followed by other sensory modality (e.g., texture). This method has been proposed by (Agudelo, Varela, & Fiszman, 2015) and applied in some food products; but had not been systematically compared to the other methods before.

Time standardization has been proposed to remove assessor noise (Lenfant, Loret, Pineau, Hartmann, & Martin, 2009). Regardless of temporal methods used, the main results consist of temporal curves (i.e. curves of the evolution of the proportions for each attribute over time) and product trajectories (i.e. the evolution in how the sample was characterized over time).

Temporal curves

For each point of time, the proportion of runs (subject*replication) for which the given attribute was assessed as dominant (for TDS) or applicable (for TCATA) is computed. These proportions are smoothed and plotted against time. The curves are called temporal curves. Traditionally, TDS analyses use chance and significant level calculated by binomial tests (Pineau et al., 2009); TCATA analyses employ two-sided Fisher-Irwin test (Castura, Antúnez, et al., 2016) to obtain the conclusion of an attribute as significant during a specific time duration. The issue with the current approaches is that these analyses violate some assumptions: *independence* for TDS data, and *prior chance probability* for TCATA data. Randomization test (Edgington & Onghena, 2007), however, does not rely on any parametric assumptions, can be a useful strategy for analyzing this kind of data. For further discussion, the reader is referred to (Meyners & Castura, 2018a; Meyners & Pineau, 2010).

Product trajectories

By linking adjacent time points corresponding to the same product and applying multivariate analyses such as PCA or CA on the citation rates at different time points, product trajectories visualize the evolution in how the sample was characterized in sensory space over time (Lenfant et al., 2009). Generally, PCs are found to explain maximum variability (dispersion of products). However, in some cases of temporal data, the first PC does not capture the variability of products, but rather a "mean citation proportion" dimension which contracts low citation proportions at the start/end of the evaluation with relatively large mean citation proportions at the middle of the evaluation (Castura, Baker, & Ross, 2016). Thus, care should be taken in interpreting the product trajectories to avoid any misleading (Beaton & Meyners, 2018).

Consumer expectations

Definition of satiation and satiety

Satiety comprises two processes: satiation (intra-meal satiety) and satiety (post-ingestive satiety or inter-meal satiety). The former is defined as the process that leads to the termination of eating; therefore, controls meal size; the latter, on the other hand, is the process that leads to inhibition of further eating, decline in hunger, increase in fullness after a meal is finished (Blundell et al., 2010).

Satiation can be measured through the measurement of ad libitum food consumption of particular experimental foods (weight in grams or energy in kcal or kJ) under standardized conditions. Satiety can be measured by tracking changes in subjective need states over time (i.e., hunger/fullness/desire to eat) or by measuring the duration between the treatment and the next meal; the intake at the next meal following the experimental treatment (Chapelot, 2013; Forde, 2018).

Effects of texture attributes and food reward on satiating perceptions

Satiation and satiety are controlled by a cascade of sensory, cognitive, post-ingestive and post-absorptive signals that begin with the consumption of a food and continue as the food is digested and absorbed (Blundell et al., 2010; Kringelbach, Stein, & van

Hartevelt, 2012); namely the Satiety Cascade, which depicts satiety as a time-dependent process.

Texture attribute

Based on the Satiety Cascade (Blundell, 1991) and Food intake cycles (Kringelbach et al., 2012), sensory perception is a key fundamental factor for both satiation and satiety. Among sensory dimensions, texture determines expectations of satiation and satiety further than flavour does (Chambers, 2016; Hogenkamp, Stafleu, Mars, Brunstrom, & de Graaf, 2011). Food texture can influence at several levels. First, texture plays a critical role in satiation or satiety through its effect on oro-sensory exposure (McCrickerd, Chambers, Brunstrom, & Yeomans, 2012; Tang, Larsen, Ferguson, & James, 2017). More specifically, longer mastication duration and higher intensity of sensory signals are also linked to higher satiation (Blundell et al., 2010; Bolhuis, Lakemond, de Wijk, Luning, & Graaf, 2011). Second, from a cognitive perspective, people may think solid foods are more satiating than liquid foods, i.e. solid foods will contain more energy than liquid foods, without necessarily reflecting their actual calories (de Graaf, 2012).

Food reward

Berridge and colleagues (Berridge, 1996, 2007) have provided a useful framework of food reward, and its role in satiation and satiety (Dalton & Finlayson, 2013). Food reward comprises multiple sub-components, including effective pleasure component and a non-affective motivational component, termed “liking” and “wanting”, respectively (Finlayson & Dalton, 2012). Liking is described as the pleasure of eating a food and wanting as the drive to eat triggered by a food cue (Dalton & Finlayson, 2014). Both can be assessed implicitly or explicitly, but the most used measures are explicit liking, the hedonic experience (Pool, Sennwald, Delplanque, Brosch, & Sander, 2016). While people tend to be very good at estimating and reporting their liking for food, they are often unable to accurately gauge their implicit wanting for food (Dalton & Finlayson, 2013). The illustration how homeostatic and hedonic system linked to each other is viewed in an integrated psychobiological system; these psychological processes have a major influence on food intake but seem to function differently (Finlayson & Dalton, 2012).

Evidently, liking and wanting affect satiation and satiety and food intake. Yet, the ways in how these expectations are related are still unclear; while some studies show that if people eat a food they greatly enjoy, they will experience more pleasure, satiation and satiety (Bobroff & Kissileff, 1986; Mattes & Vickers, 2018; Rogers & Schutz, 1992), others observe that increased liking decreased feelings of satiety or satiation (Hill, Magson, & Blundell, 1984; Holt, Delargy, Lawton, & Blundell, 1999).

Expectations instead of actual measures

In human subjects, food is emptied into the duodenum for absorption at a rate of only about 10 kJ/min (Carbonnel et al., 1994). This greatly constrains the opportunity for physiological adaptation and the detection of energy as a meal proceeds. To overcome this problem, people often use their prior experience to moderate intake as well as satiation. In other words, meal size is controlled by the decisions about portion size, before a meal begins. Thus, satiation might be determined by the volume of food that is consumed rather than its energy content (Brunstrom, 2011). Moreover, in recent studies, some authors have shown that people have very precise expectations about satiety and satiation that foods are likely to confer (Brunstrom & Rogers, 2009; Brunstrom & Shakeshaft, 2009; Brunstrom et al., 2008). For these reasons, expectations of satiation and satiety without consuming a whole portion have been used to measure satiation and satiety in many studies (de Graaf, Stafleu, Staal, & Wijne, 1992; Fiszman & Tarrega, 2017).

In general, expected satiation can be quantified by selecting the amount that would be required to feel full (Forde, Leong, Chia-Ming, & McCrickerd, 2017), whereas expected satiety can be quantified by asking the participant to imagine consuming the portion of food and rate how long they would expect to be full (Forde, 2018). Ideal portion-size can be assessed by asking the participant to select the amount that they would typically consume or the amount that they would like to consume at that moment (Wilkinson et al., 2012).

Satiety-related perceptions and portion size selection

The role of liking as a contributor to meal size, as other factors, such as satiation and satiety, has been considered in many studies. However, it is still far from consensus and has been debated over different studies. Some studies indicate that reducing the palatability of our diet should result in reduced food consumption (Yeomans, Blundell, & Leshem, 2004). Likewise, incremental increases in palatability lead to short-term overconsumption; that is, we consume more of foods that we like (Cooke & Wardle, 2005; Yeomans, 2007). Nevertheless, other studies find that palatability was not associated with the selection of portions and then rejected the hypothesis of these palatable foods tend to be selected in relatively larger portions (Brunstrom & Rogers, 2009).

In addition, these factors (i.e., liking, satiation and satiety) as considered separately, explain a relatively small amount of total variance in food intake (de Castro, 2010). Therefore, the integration of liking, satiation and satiety can be regarded as a good approach to address the question whether “quality can replace quantity”.

Consumer attitudes

Attitudes related to healthfulness and taste of food

Consumer populations can be segmented on the basis of their food orientations, particularly attitudes (Contento, Michela, & Goldberg, 1988). Several instruments that measure food-related attitudes have been developed such as Food Neophobia scale (Pliner & Hobden, 1992) or Food Choice Questionnaire (Steptoe, Pollard, & Wardle, 1995). These studies indicate that health is an important factor which people take into account when choosing their food (Glanz et al., 1993). Besides the healthfulness of foods, taste has been found to be a key predictor of food consumption (Brug, Debie, van Assema, & Weijts, 1995; Koivisto & Sjödén, 1996). Considering both two factors (i.e. healthfulness and taste), Roininen and colleagues (Roininen, Lahteenmaki, & Tuorila, 1999) developed and validated the Health and Taste Attitudes Questionnaires which assess consumers’ orientations toward the health and hedonic characteristics of foods. This questionnaire includes: (1) three health-related factors, labeled as “General health interest”, “Light product interest” and “Natural product interest”; (2) three taste-related factors, named “Craving for sweet foods”, “Using food as a reward” and “Pleasure”.

Hunger and fullness sensations

An understanding of the subjective experiences of hunger and/or inhibition of fullness is important to the accurate measurement of the satiety that a food provides (Murray & Vickers, 2009). Hunger and fullness have both physical and psychological components (Harris & Wardle, 1987; Mattes & Friedman, 1993). These components (e.g., hunger, fullness, desire, prospective consumption) can be measured by the use of line scales as proposed by (Blundell et al., 2010). Recently, the 5-Factor Satiety Questionnaire has been developed by Karalus and colleagues for measuring hunger and fullness feelings both physical and mental components as well as liking of the foods (Karalus, 2011; Karalus & Vickers, 2016).

Path modelling as a holistic approach to predict portion size selection from other consumer aspects

As mentioned previously, expected satiation, satiety and hedonic quality influence each other and together they influence portion size. This type of data could be modelled by PLS-PM approach as proposed by Wold and colleagues (Wold, 1975a, 1975b; Wold, 1985). A detailed review of PLS-PM is given in some books and papers. Thus, this part of the thesis provides a summary of most important features of PLS-PM. Besides that, the alternative approach, namely SO-PLS-PM (Næs, Tomic, Mevik, & Martens, 2011), is proposed to solve some limitations of PLS-PM.

PLS path modelling

The principle behind PLS-PM is that iterative algorithm estimates the relationships among blocks of observed variables, through the construction of non-observed variables. In many cases, the observed variables (i.e. manifest variables MVs) in individual blocks are very numerous and inter-correlated. Thus, direct fitting of data blocks to each other by, for instance, least squares becomes impossible. This is handled by the so-called non-observed variables (i.e. Latent variables LVs) which describe the main variability in the MVs. Simple and multiple regressions are applied to estimate the relationships between these variables (Vinzi, Chin, Henseler, & Wang, 2010). In PLS-PM, the relations are described by the two following models: the structural model and the measurement model (Chin, 1998; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005; Wold, 1980).

From PLS-PM, some essential results should be obtained: the relations between LVs (i.e. path coefficients including both strengths and directions); direct, indirect and total effects as well as the explained variances for each LV.

SO-PLS path modelling

Within the PLS approach, there is an underlying assumption of uni-dimensionality of the different blocks (Tenenhaus et al., 2005; Vinzi, Trinchera, & Amato, 2010). However, very often for sensory and consumer data, products are characterized by several attributes and consumers can be combined in different groups. Consequently, the data sets are multi-dimensional in nature and then the uni-dimensionality assumption is not satisfied. A solution could be dividing blocks of data by using some dimensional reduction methods (e.g., PCA). Yet, it is not an easy task to decide how many uni-dimensional blocks (i.e. PCA components) should be kept.

From these issues, SO-PLS approach (Næs et al., 2011) is proposed as an alternative. This method is based on splitting the estimation process into a sequence of multi-block modelling steps for each dependent block (endogenous) versus its predictive/input blocks. In other words, the estimation is based on sequential use of orthogonalization and PLS regression (Menichelli, Almøy, Tomic, Olsen, & Næs, 2014). By doing so, it allows blocks with several components (i.e. multi-dimensionality); therefore, it is possible to use original data instead of PCA factor scores obtained by the data preprocessing (applied in PLS-PM). Also, PCP method (Langsrud & Næs, 2003) is used to interpret the relations within and between blocks of data.

As opposed to PLS-PM, validated explained variances are used as "path coefficients" to explain the relations between blocks of data in SO-PLS-PM.

Other statistical methods

Apart from PLS-PM and SO-PLS-PM used in path modelling, some other statistical methods (e.g., PCA, MFA, CVA, MANOVA) are performed to analyze data in this thesis. Particularly, PCA is used to display product trajectories; MFA for obtaining sensory maps; CVA and MANOVA in the interpretation of panel performances.

Principal Component Analysis (PCA)

PCA (Jolliffe, 2002; Mardia, Kent, & Bibby, 1979) is based on the idea of finding the most important directions of variability in high-dimensional space of all the measured variables (Næs, Brockhoff, & Tomic, 2010). There are several ways of doing PCA for a data block $\boldsymbol{X}$, in this thesis focus will be on SVD (Abdi, 2007). The data block $\boldsymbol{X}$ comprises

I observations described by J variables and it is represented by the $I \times J$ matrix $\boldsymbol{X}$. The matrix $\boldsymbol{X}$ has rank L where $L \leq min\{I, J\}$. Mathematically, the SVD of matrix $\boldsymbol{X}$ decomposes it into three matrices as:

$$\boldsymbol{X} = \boldsymbol{U}\boldsymbol{\Gamma}\boldsymbol{V}^T \text{ with } \boldsymbol{U}^T\boldsymbol{T} = \boldsymbol{V}^T\boldsymbol{T} = \boldsymbol{I} \tag{1.1}$$

where $\boldsymbol{U}$ is the $I \times L$ matrix of left singular vectors, $\boldsymbol{V}$ is the $J \times L$ matrix of right singular vectors, and $\boldsymbol{\Gamma}$ is the $L \times L$ diagonal matrix of L singular values.

Factor scores $\boldsymbol{F}$ is obtained by:

$$\boldsymbol{F} = \boldsymbol{U}\boldsymbol{\Gamma} = \boldsymbol{X}\boldsymbol{V} \tag{1.2}$$

The matrix $\boldsymbol{V}$ is also called a loading matrix.

Multiple Factor Analysis (MFA)

MFA (Escofier & Pagès, 1994), a part of the multi-table PCA family, is to analyze K blocks of variables ($\boldsymbol{X}_k$) collected on the same set of observations. The analytical tool is also the SVD and GSVD, a generalization of SVD (Abdi, Williams, & Valentin, 2013).

MFA consists of three main steps:

- Step 1: each block $\boldsymbol{X}_k$ is decomposed using SVD, and the first singular value $\gamma_{1,k}$ of each block is recorded. The weight α_k is equal to the inverse of the first squared singular value, and the matrix $\boldsymbol{A}$ is defined for GSVD in step 2.

$$\alpha_k = \frac{1}{\gamma_{1,k}^2} = \gamma_{1,k}^{-2} \tag{2.1}$$

$$\boldsymbol{A} = diag\{[\alpha_1 \mathbf{1}_1^T, \dots, \alpha_k \mathbf{1}_k^T, \dots, \alpha_K \mathbf{1}_K^T]\} \tag{2.2}$$

  where $\mathbf{1}_k$ is a vector of ones representing the variables in block $\boldsymbol{X}_k$.
- Step 2: GSVD of $\boldsymbol{X}$ under the constraints provided by $\boldsymbol{M}$ and $\boldsymbol{A}$ is computed:

$$\boldsymbol{X} = \boldsymbol{P}\boldsymbol{\Delta}\boldsymbol{Q}^T \text{ with } \boldsymbol{P}^T\boldsymbol{M}\boldsymbol{P} = \boldsymbol{Q}^T\boldsymbol{A}\boldsymbol{Q} = \boldsymbol{I} \tag{2.3}$$

  where $\boldsymbol{P}$, $\boldsymbol{Q}$, $\boldsymbol{\Delta}$ play the roles of $\boldsymbol{U}$, $\boldsymbol{V}$, $\boldsymbol{\Gamma}$ in the SVD decomposition, respectively;
  $\boldsymbol{M}$ denotes an $I \times I$ positive definite matrix representing the 'constraints' imposed on the rows of an $I \times J$ matrix $\boldsymbol{X}$;
  $\mathbf{A}$ is $J \times J$ positive definite matrix representing the 'constraints' imposed on the columns of $\boldsymbol{X}$.
  The MFA factor scores $\boldsymbol{F}_{MFA}$ are calculated:

$$\boldsymbol{F}_{MFA} = \boldsymbol{P\Delta} = \mathbf{XA}\boldsymbol{Q}_{MFA} \quad (2.4)$$

- Step 3: when $\boldsymbol{Q}_{MFA}$ is expressed as a column block matrix of the right singular vectors corresponding to each block,

$$\boldsymbol{Q}_{MFA} = \begin{bmatrix} \boldsymbol{Q}_1 \\ \cdots \\ \boldsymbol{Q}_k \\ \cdots \\ \boldsymbol{Q}_K \end{bmatrix} = [\boldsymbol{Q}_1^T | \dots | \boldsymbol{Q}_k^T | \dots | \boldsymbol{Q}_K^T]^T \quad (2.5)$$

the partial factor scores of a block $\boldsymbol{F}_k$ are defined from the projection of this block onto its right singular vectors $\boldsymbol{Q}_k$.

$$\boldsymbol{F}_k = K \times \alpha_k \times \boldsymbol{X}_k \boldsymbol{Q}_k \quad (2.6)$$

Canonical Variate Analysis (CVA)

Unlike PCA, CVA focuses on observations classified into g groups, considering both between and within group variation. The principle behind CVA is to find linear combinations of original variables which maximize the variation between groups, relative to the variation with groups (Gower, Lubbe, & Roux, 2011; Mardia et al., 1979).

Consider g groups of data, with v variables measured on each of n_k individuals for the k^{th} group. Let x_{km} represent the vector of observations on the m^{th} individual for the k^{th} group ($m = 1, \dots, n_k;\ k = 1, \dots, g$).

Sum of squares and products (SSQPR) for the k^{th} group is defined as:

$$\boldsymbol{S_k} = \sum_{m=1}^{n_k} (x_{km} - \bar{x}_k)(x_{km} - \bar{x}_k)^T \quad (3.1)$$

where $\bar{x}_k$ is mean value of variables in the k^{th} group

$$\bar{x}_k = \frac{1}{n_k} \sum_{m=1}^{n_k} x_{km} \quad (3.2)$$

Then, the variation within groups $\boldsymbol{W}$ and between groups $\boldsymbol{B}$ are determined:

$$\boldsymbol{W} = \sum_{k=1}^{g} \boldsymbol{S}_k \quad (3.3)$$

$$\boldsymbol{B} = \sum_{k=1}^{g} n_k(\bar{x}_k - \bar{x}_T)(\bar{x}_k - \bar{x}_T)^T \tag{3.4}$$

where

$$\bar{x}_T = \frac{1}{n_T}\sum_{k=1}^{g} n_k\bar{x}_k \tag{3.5}$$

$$n_T = \sum_{k=1}^{g} n_k \tag{3.6}$$

Multivariate Analysis of Variance (MANOVA)

MANOVA is a generalization of ANOVA to a situation in which there are several dependent variables (Mardia et al., 1979). MANOVA tests whether mean differences among groups on a combination of dependent variables are likely to have occurred by chance (Huberty & Petoskey, 2000). In general, MANOVA comprises two steps (Tabachnick & Fidell, 2013):

- Step 1: A new dependent variable is created as a linear combination of measured dependent variables, while maximizing differences between groups.
- Step 2: ANOVA in then performed on the new dependent variable; that is, testing of the hypothesis of no difference between the groups.

Summary of results

Paper 1

This study aimed at exploring the role of texture of solid foods in consumers' perception and expectations of satiation and satiety; in particular, the role of dynamic perception during oral processing, with barley bread as a case study. Eight barley bread samples were manufactured at Nofima's pilot bakery, using the same formulation and ingredients but manipulating the texture of the final products by changing process parameters (i.e. barley type, barley size, treatment, fermentation). This resulted in products varying in texture and being equi-caloric.

Eight bread products were first characterized by a trained panel using TDS method, and then four products were selected for the next descriptive task (QDA® task). Finally, a consumer test was conducted to evaluate liking, expected satiation, expected satiety and answered to the a CATA question. The consumer questionnaire can be found in Appendix 1.

By comparing static and temporal descriptive results, some attributes were described very differently between TDS and QDA® approaches. *Juicy*, for example, presented very similar intensity ratings for the four samples in the QDA; however, the individual TDS plots showed that juiciness was dominant at different points of the mastication. Time duration was split into three time intervals: beginning, middle, end. MFA was applied on time interval data to obtain sensory maps, characterizing the relationships between products and temporal dynamic attributes during three stages of the mastication. Penalty-lift analysis was performed to highlight the drivers of expected satiation and expected satiety. Among sensory attributes, *compact*, *coarse* and *heavy* as the most important drivers of expectations of satiety and satiation for consumers, while *aery/fluffy* and *not coarse* were inhibitors of those perceptions.

The results of this paper demonstrated that manipulating texture of (semi)solid products looks as a promising way to develop food products perceived as more satiating and lower in calories.

Paper 2

Dynamic sensory methods have been developed and optimized to describe the evolution of sensory properties during the mastication. All these methods have some advantages and limitations. The objective of this work was to compare three temporal methods (TDS, TCATA and M-TDS) based on detailed criteria consisting of dynamic profile, product trajectory and panel performance.

Eight yoghurt products were prepared from a design of experiments varying parameters: viscosity (thin/thick), particle size (flakes/flour) and flavour intensity (low/optimal). Nofima's panel evaluated products by both static and temporal methods in the four following tasks: QDA®, TDS, TCATA and M-TDS. The data was analyzed in terms of sequence of time points and aggregation of time intervals.

Considering temporal curves, the main difference arose as focusing on the attributes related to sweetness perceptions (i.e. *sweet*, *vanilla*). While TCATA and M-TDS could point out these perceptions as applicable or dominant attributes, TDS failed to indicate these as dominant attributes in products with different levels of flavouring. Added to this, although product trajectories showed the similar evolution patterns among methods, TDS was less resolved than other methods.

When testing panel performance, two criteria were considered: discrimination and agreement abilities. CVA, based on a MANOVA model (product as fixed effect, subject as a random effect), was conducted to show the product configurations in which the sizes of confidence ellipses and the overlapping between confidence ellipses around each product represented the agreement and discrimination abilities of panel, respectively. From that, it was suggested that TCATA and M-TDS were better than TDS in both two criteria, and these two methods described samples in larger number of attributes as compared to TDS.

Paper 3

Expectations of satiation and satiety, along with liking, can modulate portion-size selection, and then food intake. However, the way how these factors interact and affect portion-size selection has not been unveiled. Considering all these expectations in the prediction model, this study aimed at better understanding these complex relations by simultaneously assessing the relative influence of consumer characteristics and product related properties on portion size selection.

Eight yoghurt products were prepared in the same way in Paper 2. One-hundred-and one consumers were recruited for a consumer test. Consumers answered questions regarding consumer characteristics (e.g., attitudes to health and hedonic characteristics of foods; feelings of hunger and fullness). In an evaluation step, they tasted eight yoghurt products and rated liking on LAM scale, expected satiation on SLIM scale, expected satiety on 6-point scale. Based on the size of a commercial yoghurt, they rated their prospective portion size. The portion-size scale was one-third to three-times as compared to a normal size container. Also, consumers were classified into four groups of their preferred mouth behaviour: *Cruncher*, *Chewer*, *Sucker* and *Smoosher* using the JMBM™ tool. The consumer questionnaire and scales can be found in Appendix 2, 4.

Data comprised different blocks: consumer and product characteristics. Yet, the focus was on the block of product-related variables. To deal with the assumption of uni-dimensionality in PLS-PM, for each block, PCA on double-centered data was applied, and then PCA scores on the first two components (*viscosity*, *particle-size* components) were recorded. These PCA scores were used as input to the path model.

Regardless of whether viscosity or particle-size was considered, the prediction model pointed that liking played an important role in predicting portion selection; the higher the liking the bigger portion selection. Also, satiation and satiety contributed to the relation of liking-portion both in direct and indirect ways. Yet, the interpretation should be taken with care due to multiparametric nature of these expectations.

PCA was applied to solve the multi-dimensionality issue, but it was not easy task to decide how many dimensions remained. Other methods such as SO-PLS and Path-ComDim have been proposed to handle multi-dimensional data. Future research should be conducted to compare and deeper understand advantages and limitations of these methods.

Paper 4

To understand consumers' portion size selection, a holistic approach is required where several aspects of consumer expectations could be considered simultaneously (i.e. liking, expected satiety, expected satiation). This kind of data should be subjected to multiblock modelling methods, which investigate the relations among data blocks and highlight which exploratory blocks are important in predicting the response block. In this sense, PLS-PM has been found as a good tool to model this relation. However, product properties and consumer characteristics are described multi-dimensionally, leading to multi-dimensional blocks in the data set. That violates assumption of uni-dimensionality of the reflective mode in PLS-PM. As alternative and more exploratory approach based on the SO-PLS for multiblock regression analysis, SO-PLS-PM is proposed to handle the uni-dimensionality issue and explain the relations between original data blocks without any preprocessing of the data. In this context, this paper aims at comparing the results obtained by PLS-PM and SO-PLS-PM for data sets with different complexities. Two data sets (yoghurt and biscuit case studies) were collected in two consumer tests. Consumers were asked to taste the products and rate their liking, expected satiation, expected satiety and prospective portion size. The consumer questionnaires and scales can be found in Appendix 2, 3, 4.

For the less complex data (semisolid samples: yoghurt), both PLS-PM and SO-PLS-PM pointed out that liking was the essential driver of satiation and portion selection, while satiation mainly predicted satiety. These results were in accordance with the findings of Paper 3. However, when the complexity of the samples increased (solid samples: biscuits), some differences between PLS-PM and SO-PLS-PM appeared in the modelling. The main differences were the relations *Liking-Satiation* and *Satiety-Portion* which were significant in PLS-PM, but not in SO-PLS-PM. The possible explanation could be that the standard PLS-PM is more prone to overfitting.

From these results, SO-PLS-PM reveals the ability to model multi-dimensional data blocks without any preprocessing of the data. Also, that makes interpretation of the model more explicit and easier to understand.

Discussion and future perspectives

Traditionally, sensory perceptions have been described by static methods using trained panels (e.g., QDA®) or consumers (e.g., CATA). However, sensory perceptions are not static, but dynamic in nature. Sensory attributes are perceived in a specific order during oral processing, depending on both food structure and human oral behavior. Dynamic sensory perception involves the perception of multiple attributes at a time, their order of appearance throughout time and their relative importance during consumption. Considering these aspects helps to describe the product during consumption, with a close relation with the food oral process. Then, these dynamic perceptions could be used to determine the drivers of consumers' preferences and other expectations determined by the eating behaviour. Added to this, it has recently been observed that dynamic sensory perception can play an important role in consumer's perception of satiety. These consumer expectations (i.e. liking, satiation, satiety) relate to each other and affect food intake in general or portion-size selection in particular. For that reason, it would be very important to better understand the interrelation of the dynamic sensory perception with consumers' expectations, preferences and perception of satiety.

The findings from this thesis have practical implications; in particular, development of healthy products of enhanced satiety that consumers choose and like could allow a better control of eating behavior and better public health. This is of interest for food companies and health authorities. Added to this, methodological exploration in the thesis, both from data collection and data analyses points of view can be translated in method recommendations in academic research.

In the next part, comprehensive discussion and some future perspectives would be provided.

Temporal methods for sensory profiling

Comparison between methods

To compare temporal methods, some criteria have been used in this work including product description, product trajectory, and various criteria for assessing panel performance. From a descriptive point of view, TCATA provided better results than TDS, as this method captures applicable attributes at a given time and describes the products dynamic perception in greater detail. The key difference between TDS and TCATA are the way how assessors select attributes: one dominant attribute in TDS, two or more applicable attributes in TCATA. More specifically, this can mean that different sensory modalities (e.g. flavour and texture) are in competition for the 'dominance' rating in TDS task (Varela et al., 2017). However, many products could have one flavour and one texture attribute dominating at the same time, due to the fact that flavour and texture are really perceived by different channels, chemesthesis (chemically induced sensations in the oral and nasal cavities) vs. somesthesis (tactile and thermal sensations) (Lawless & Heymann, 2010b). Therefore, this is a complex decision which assessors need to do, leading to the loss of descriptive information and the low agreement in TDS as a result.

An attempt to deal with the dithering and dumping in TDS tasks, a modality based TDS (M-TDS) was carried out in this thesis and its results were also compared to those of TDS and TCATA. M-TDS stills focuses on the dominant attributes but can describe products in more detail, as different modalities can be addressed for the same product. In this sense, M-TDS requires sequential steps, for example, flavour temporal evaluation followed by texture temporal evaluation. Yet, it is not straightaway for assessors to separate their perceptions into different modalities and to evaluate sensory perception in each modality. The results obtained in this thesis show that M-TDS can be more effective than TDS in highlighting relevant attributes and in discrimination ability, however, in a more recent study, M-TDS has been shown to be less discriminative than TDS when looking at data by time points (Meyners, 2018), so more research would be needed to draw general conclusions on discriminative ability. Furthermore, the interaction between sensory modalities when applying M-TDS is not taken into account when evaluating dominance of sensory attributes on different modalities in isolation, what could bias the M-TDS results. For these reasons, M-TDS seems to be less valid from an ecologic perspective, and its usefulness is still to be proved until these above issues are addressed.

Added to this, one method should not be considered as an equal alternative to other methods because these methods are based on different conceptual aspects (applicability vs. dominance). Consequently, the choice of method should be considered in a specific situation depending on the purpose of the study. If researchers look for information about the attribute that draws the most attention, TDS is recommended. In contrast, TCATA is a better method when more detailed descriptive information is required.

During the development of satiety-related products, it is often required to identify the sensory attributes which influence satiety perception. TCATA is highly suggested in this case to capture the most detailed picture of the dynamic perceptions over time.

Further considerations when comparing dynamic methods

Regardless if TDS or TCATA is used, results are obtained based on some assumptions which are not always satisfied in the real data collection setting. In the next part, these are discussed in more detail together with some potential solutions.

Definition of dominance in TDS

The TDS methodology entirely relies on the capacity of the assessors to select a dominant perception during mastication. The definition of dominance is therefore a key point of the TDS method (Varela et al., 2017). In the literature, several definitions have been given such as 'popping-up' (Pineau et al., 2009), the sensation that 'triggers the most your attention' (Le Révérend, Hidrio, Fernandes, & Aubry, 2008; Lenfant et al., 2009), or 'the most intense' sensation (Labbe et al., 2009).

Among those, the intensity measurement in TDS has been not recommended, because of mixing up two different cognitive processes: the selection of a dominant attribute (qualitative task) and the intensity scoring (quantitative task) (Schlich & Pineau, 2017). The definition 'triggers the most your attention' has been mostly used in TDS studies; however, it is still not clear how assessors select the attributes: trained assessors mainly refer to the dominant attribute as the one that caught their attention and that can be for varying reasons (new one popping up, change of modality, change in intensity), consumers consider intensity as the main aspect of sensory perception involved in the assessment of dominance (Varela et al., 2017). Some authors argue that dominance, as understood by consumers, would be linked to preference and drivers of liking (Schlich & Pineau, 2017), however, this has not been substantially proved, and more research is needed in this sense. The fact that assessors within a panel may evaluate dominance relying on different concepts, makes TDS data highly noisy (Varela et al., 2017).

For that reason, a very important thing in TDS tests would be to agree in a consensus definition of dominance among the assessors.

Statistical assumptions in TDS and TCATA

The rationale behind temporal methods is to capture the dynamic perceptions over time responding at different stages of the mastication. For example, when a solid product (e.g., biscuit) is introduced into the mouth, first it is perceived as hard/crunchy, then dry/rough, and finally pasty/cohesive. These perceptions respond to the following stages: reducing particles, mixing smaller particles with saliva, and obtaining a suitable bolus for swallowing (Witt & Stokes, 2015). Consequently, at a given time in the oral process, the probability of selecting one attribute as dominant would be higher or lower than others. This point violates the underlying assumption for obtaining the chance level in TDS calculations, which assumes that attributes are randomly selected and equally dominant (Pineau et al., 2009). This violation could potentially lead to misinterpretation of TDS results. To handle this issue, recently, Meyners and colleagues (Meyners & Castura, 2018b) have proposed an alternative approach based on randomization test to display the dominant attributes in TDS plots. Instead of chance and significant lines, the reference lines are used to determine the dominant attributes. Besides that, this approach focuses on both high and low dominance rates which are statistically significant differences as compared to reference lines.

Likewise, this approach can be applied to TCATA data (Meyners & Castura, 2018a). By doing so, the results from both TDS and TCATA are more concise and comparable.

Interpretation of product trajectories

Product trajectories are used to highlight the evolution of the products over time. They are obtained by using both PCA or CA (Castura, Antúnez, et al., 2016; Castura, Baker, et al., 2016). It is usual practice to look into the first two components to look into the temporal trajectory of the products in mouth (Devezeaux de Lavergne et al., 2016; Mayhew, Schmidt, Schlich, & Lee, 2017; McMahon, Culver, Castura, & Ross, 2017; Reyes, Castura, & Hayes, 2017; Tang et al., 2017; van Eck, Fogliano, Galindo-Cuspinera, Scholten, & Stieger, 2018). However, it may be required in some cases to investigate other PCs that describe less (or relatively little) variance to clearly understand the product evolution. It is not straightforward task to decide how many components would need to be considered.

The product trajectories from Paper 2, for example, were displayed by the components 1 and 3 which showed the clear separations better than those based on the first two components. This thesis highlights the importance that the selection of components should depend on the interpretability and relevance of product trajectories rather than how much variability is explained by each component.

In a very recent paper, Beaton and colleagues (Beaton & Meyners, 2018) suggested another approach to solve this issue. Instead of PCA and CA, they used ConCA which removed temporal effects before applying CA on TCATA data. With this approach, product trajectories are plotted only against sensory perceptions.

Transition of dominant attributes

As usual, temporal data are analyzed to display temporal curves and product trajectories. It is also possible to investigate the data with respect to the transition of one dominant attribute to another. This analysis was initially proposed by (Franczak, Browne, McNicholas, Castura, & Findlay, 2015) using discrete Markov chains. Recently, Lecuelle and colleagues used semi-Markov chains to represent chronological main transitions between attributes (Lecuelle, Visalli, Cardot, & Schlich, 2017, 2018). This approach may help to deeper understand the way how dominant perceptions change over time. Yet, it still lacks a statistical test to check the significance of the transition probabilities. Without a significance test, it is quite difficult to conclude that one transition is significant or not. Attribute transitions could be of interest when one is looking into oral processing and the perceptions determined by it; for instance, it could be that some attribute transitions could be linked to the transformation to the bolus state during the mastication, or some could be more prone to happen before swallowing, etc. This could be potentially utilised to better understand satiety-related perceptions and use the information for texture modifications and product reformulation.

Texture as driver for satiety-related perceptions

Although satiation and satiety measure different concepts of satiety-related perceptions, the results of this thesis show that consumers often use texture attributes (e.g., *compact*, *coarse, heavy*) as drivers of these expectations. That implies the importance of oral processing in satiation/satiety perceptions, which in turn, give cues for portion-size selection. In other words, expectations of satiation and satiety could be modified by changing texture attributes of products while keeping calories equal. These results have been observed in solid products (barley bread in this study), but also in semi solid products. For example, Morell and colleagues indicated that consumers related satiety more with the thick and creamy characteristics at the beginning of the consumption of smoothies than to the loss in structure in the rest of the consumption (Morell et al., 2014).

In this thesis, the drivers of liking, the relations among expected satiation and expected satiety were considered (yoghurt case study). The results were in agreement with those of the solid product (barley bread study) in which texture attributes (*Thick, Creamy, Dense*) lead to an increase in both expected satiation and satiety for equicaloric and equi-composition samples. When considering liking ratings, flavour attributes instead (*Sweet, Vanilla*) were found as main drivers. It is reasonable due to the fact that consumers many times pay most attention to liking of flavour when evaluating overall liking (Andersen, Brockhoff, & Hyldig, 2019).

The modelling of portion-size selection

Liking as the main effect

For both yoghurt and biscuit case studies, liking was found as the key factor which imparted on portion-size selection. The prediction path model pointed out that an increase in liking would lead to an increase in prospective portion size. In addition, liking could have an influence on satiety through satiation; however, the strengths of the relations depend on the complexity of the data. The relation was well explained when sensory dimensions were well defined by the data (yoghurt data). However, the model was not easily interpreted when the meanings of data dimensions were not explicit (biscuit data). This is a possible limitation of preprocessing data in PLS-PM approach when a few PCs cannot explain the whole information of the data.

It is important to note that the results were achieved in terms of both direct and indirect effects. In fact, when the interactions are included in the model, the interpretations become very complicated and the model needs to be considered carefully. Nevertheless, with the path modelling approach, the question of whether "quality can replace quantity" gets some answer, although it is not straightforward.

In addition, it is important to investigate the influence of individual differences on the prediction model. The results from Paper 3 pointed out that different MB groups (i.e. chewer, cruncher, smoosher) rated satiation differently (interaction product-mouth behavior) and predicted Portion size from Liking in different ways. In particular, smooshers were more discriminative when rating expected satiation in yoghurts, suggesting that the managing of the samples between the tongue and the upper palate could make them more aware of the flavour and particle size as drivers of satiation. In the portion size modelling, while the relation Liking-Portion was positive and strong for chewers and crunchers, it resulted to be weak and negative for smooshers. Added to this, chewers and crunchers seemed to use both two sensory dimensions (*viscosity* and *particle-size*) for estimating the Portion size, while smooshers used particle-size only. This suggests that the way consumers chew their food has an impact on their texture perception of that food, and then affect their expectations (i.e. liking, portion in this case). This is in agreement with previous studies (Jeltema et al., 2015, 2016), that suggest that consumers use different strategies to manipulate foods and this influence their expectations. As texture has been considered as the main reason for food rejection (Drewnowski, 1997) and food aversion (Scott & Downey, 2007), a better understanding of how different oral processing behaviours (mouth behaviour, eating rate, etc.) relates to sensory perceptions and consumer expectations would aid in product development with controlled texture attributes. The results of this thesis add to this hypothesis, and show it could be particularly important when designing products of enhanced satiety, to look into individual differences, as they may underlie how consumers draw their satiety expectations, and how these in turn interact with their preferences, to decide on a portion size. This will mean that "one size does not fit all" or that product reformulation may not have the same effects for everyone.

Effects of consumer characteristics on consumer expectations

In addition to consumer expectations (i.e. liking, satiation, satiety), variables related to consumer characteristics could be included in the prediction model. Considering yoghurt data, for example, higher mental fullness scores predicted larger increases in viscosity-related satiety. This result is in accordance with Mattes and colleagues, pointing out that a higher expected satiety led to a decrease in hunger and increase in fullness immediately after consuming the food (Mattes & Vickers, 2018). On the opposite side, feelings of mental fullness reduced consumers' satiations.

While mental fullness significantly influenced satiation and satiety expectations, the results showed that physical hunger can influence liking. Particularly, consumers that rated a higher physical hunger, tended to dislike yoghurts that are thicker. Note that physical hunger was measured by three questions, and one of them was "Rate the extent to which you currently feel stomach pain". A possible explanation for the negative relation *pHunger-LikingV* is that when people felt stomach pain, they would dislike products. However, the measure of physical hunger also included some other aspects such as famished and empty feelings. For that reason, more research is needed to better understand this not very intuitive relation.

Moreover, other variables such as craving, reward also contribute to changes in liking. These results support the point that liking is considered as complex concept imparted by several factors.

SO-PLS-PM to handle the multi-dimensionality in consumer data

In this thesis, data dimensionality reduction technique (i.e. PCA) was used to reduce data blocks (liking, expected satiety, expected satiation) in portion size modelling via PLS-PM approach. However, one data block of sensory properties or consumer characteristics measure some variables which not always reflect the same underlying dimensions. This block can be then regarded as multi-dimensional; one good example is overall liking. In practice, one of the most common ways to determine consumer acceptability of foods is through the measure of overall liking, this measure, however, consists of hedonic evaluations of several sensory modalities: appearance, odour, taste and texture (Andersen et al., 2019; Lawless & Heymann, 2010a) and even the consideration of non-sensory parameters could be related to its evaluation. It would be quite difficult to isolate the effect of any one sensory input without confounding it with other sensory inputs (Moskowitz & Krieger, 1995). Therefore, it seems more natural to run path models that can rely on the original data blocks, rather than the reduced data blocks obtained to ensure the assumption of uni-dimensionality.

To interpret the meanings of split data blocks, additional information is required (e.g., sensory attributes, instrumental parameters). However, many times it could be hard to explain these meanings even when additional information is available (e.g., biscuit case study in this thesis).

From these reasons, it is highly recommended to use SO-PLS-PM as a good approach to model consumer expectations; in particular, for predicting portion-size selection from liking, satiation and satiety, being particularly complex expectations. Furthermore, some other data blocks regarding consumer characteristics such as attitudes to health and hedonic characteristics of foods, feelings of hunger and fullness could be integrated into the model to better understanding portion-size selection.

Conclusions

The focus of this thesis was to better understand the relation of the dynamic sensory perception of solid and semi solid foods with consumer expectations of satiety. To do this, three research questions were explored: (1) which temporal method is appropriate to describe dynamic sensory perceptions in the light of better understanding satiety; (2) how sensory attributes affect liking, expected satiation and expected satiety and what are the drivers of these expectations; and (3) how portion-size selection can be predicted from other aspects of consumer expectations using a holistic approach that combined all these aspects.

In the light of this objectives, the main conclusions of this thesis were:

The choice of the temporal method to describe dynamic sensory perception does make a difference. Among the temporal methods investigated (TDS, TCATA and M-TDS), TCATA was highlighted as the most effective method based on two criteria: product discrimination and agreement ability. It is important to point out that TDS could be more appropriate if dominant attributes are the objective, each temporal method describes some different aspects of product profiling and the method selected depends on the purpose of the research. When a detailed temporal description is pursued (as in the case of this thesis to correlate to satiety expectations) TCATA is recommended, as it provides a more detailed response, as well as additional information about the interaction between attributes.

The effect of different sensory modalities (e.g., appearance, flavour, texture) on consumer liking and satiety-related expectations is not equal. On one hand, in the cases studied in this thesis, flavour played an important role on driving liking, but texture was, on the other hand, the main driver for satiation and satiety expectations. These effects were identified on static but also on dynamic sensory attributes. Furthermore, there are individual differences underlying these effects; different groups of consumers may have different drivers for those expectations depending on eating style, oral processing, or other eating behaviours.

Path modelling allowed to predict portion size selection as related to liking, consumer expectations of satiation and satiety, as well as consumer attitudes. Liking appeared as the main determinant of portion-size selection in the cases under study. Particularly, an increase in liking lead to an increase in prospective portion-size. Additionally, satiation showed to have a positive effect on satiety. When a standard PLS-PM was applied on preprocessed data to explain the relations between consumer expectations (i.e. liking, satiation, satiety, portion) in the model, the assumption of uni-dimensionality was violated and the interpretation of the model was not possible for complex sample sets (i.e. biscuits case study). As alternative approach, SO-PLS-PM was proposed to tackle this. Apart from solving the statistical issue, SO-PLS-PM made the relations easy to interpret in practice. For that reason, SO-PLS-PM has much potential in modelling the relations between consumer satiety-related expectations. More research would be needed in this sense, applied to further product categories of different complexities.

This thesis has laid out some methodological grounds in the area of sensometrics, looking into the relations among texture, dynamic sensory perception, and statistical modelling of portion size selection based on consumer preferences and expectations of satiation and satiety. These will allow for future work, where more research is needed in more product case studies, of different complexity, to really understand the links among consumer perceptions related to satiety and their preferences.

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Papers

PAPER 1

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Understanding the role of dynamic texture perception in consumers' expectations of satiety and satiation. A case study on barley bread

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ABSTRACT

Dynamic sensory perception has become of interest particularly related to consumers' affective response, however, better understanding the eating experience further than liking, taking into account how the dynamic sensory perception correlates to satiety perception becomes also very relevant. The objective of this work was to better understand satiety expectations in relation to the temporal aspects of texture perception during consumption. Eight barley bread samples were manufactured, with the same formulation, ingredients and caloric content but manipulating their texture by changing process parameters. A trained sensory panel evaluated the eight samples in triplicate, using a dynamic sensory method: Temporal Dominance of Sensations (TDS). Based on the results, four samples with well differentiated dynamic profiles were selected. These samples were also evaluated via classic descriptive analysis by the trained panel. A consumer test (n = 96) was run where consumers evaluated overall liking, expected satiety and expected satiation and answered to a check-all-that-apply (CATA) question that included 23 sensory and 15 non-sensory attributes. The results showed that the samples did not present mayor differences in liking but were significantly different in their expected satiety. Results showed that in solid foods like barley breads with the same ingredients, same composition and same caloric content, the oral processing, determined by textural changes, was the driver of different expectations of satiety and satiation. Dynamic textural changes responsible for driving satiety and satiation expectations were identified. Chewiness dominance mainly in the first stages of mastication and coarseness throughout the mastication were drivers of enhanced satiety perceptions, whereas a dominant perception of dryness and crumbliness at the beginning were linked to breads less expected to be satiating. A penalty lift analysis on the CATA results highlighted *compact*, *coarse* and *heavy* as the most important drivers of expectations of satiety and satiation for consumers, while *aery/fluffy* and *not coarse* were inhibitors of those perceptions.

1. Introduction

Overweight and obesity are major risk factors for various diseases, including diabetes, cardiovascular diseases and cancer. They are not only considered a problem in high-income countries, but also in middle- and low-income countries. From Global Health Observatory (GHO) data, in a global basis, around 39% of adults aged 18 and over were overweight in 2014; 13% were obese.

To control meal size and tackle overeating, there is a need to formulate healthy and satiating low-energy foods reaching consumers' acceptance. Satiety related perceptions include satiation and satiety; the former is process that leads to the termination of eating and therefore controls meal size, the latter is process that leads to inhibition of further eating, decline in hunger, and increase in fullness after a meal has finished. Compared with satiety, satiation is more strongly related to sensory attributes (Blundell et al., 2010; Lesdéma et al., 2016). The amount of intake of a particular food, however, is not solely governed by hedonic responses. It depends on the associations between sensory attributes and its metabolic consequences or expectations after consumption (Brunstrom & Rogers, 2009; Brunstrom, Shakeshaft, & Scott-Samuel, 2008). These expectations are thought to guide both portion size selection and actual food intake (Keri McCrickerd, Lensing, & Yeomans, 2015).

Recent studies (Brunstrom, 2014; McCrickerd & Forde, 2016; Wilkinson & Brunstrom, 2009) have highlighted that decisions about portion size are likely to be taken before a meal begins and that people are very good at estimating 'expected satiety' and 'expected satiation', that is, the experience of satiety is influenced more by what the person see and remembers eating, and less by what they actually ate. Brunstrom (2007, 2014) stated that the expectations of satiety and

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satiation are highly correlated with the actual number of calories that people consume, and are learned over time. Expectations are based on the complex interaction of various parameters like energy content, volume, weight, sensory properties, oral process or 'eating topography' determined by bite size, bite rate, swallow rate, etc. (de Graaf, 2011; Forde, van Kuijk, Thaler, de Graaf, & Martin, 2013).

In human subjects, food is emptied into the duodenum for absorption at a rate of only about 10 kJ/min (Carbonnel, Lémann, Rambaud, Mundler, & Jian, 1994). This greatly constrains the opportunity for physiological adaptation and the detection of energy as a meal proceeds. To overcome this problem, people often use their prior experience to moderate intake as well as satiation. In other words, meal size is controlled by the decisions about portion size, before a meal begins. Thus, satiation might be determined by the volume of food that is consumed rather than its energy content (Brunstrom, 2011).

Texture and flavor are the important dimensions of sensory perception. Between these dimensions, texture rather than flavor, determines expected satiation (Hogenkamp, Stafleu, Mars, Brunstrom, & de Graaf, 2011). From a cognitive perspective, people may think solid foods are more satiating than liquid foods, i.e. solid foods will contain more energy than liquid foods, without reflecting about their actual calories (de Graaf, 2012). Besides, texture plays a critical role in satiation or satiety through its effect on oro-sensory exposure. Due to their fluid nature, liquid foods require less oral processing time than semi-solid and solid foods, leading to reduction in oro-sensory exposure, which is important for the development of satiety related perceptions (Keri McCrickerd, Chambers, Brunstrom, & Yeomans, 2012). It is therefore essential to gain a deep understanding of how texture impacts expected satiation and satiety.

Sensory perception, however, is not a single event but a dynamic process with a series of events (Labbe, Schlich, Pineau, Gilbert, & Martin, 2009). The relation between sensations and elicited satiation is not necessarily static during consumption. For example, using milkshakes thickened with several hydrocolloids, a recent study by Morell, Fiszman, Varela, and Hernando (2014) showed that satiety expectations were closely related to consistency and creaminess at the start of the consumption in products of similar consistency but different dynamic perception in mouth. Thus, the effect of texture on satiety expectations is not a straightforward function of hard/soft or viscous/not viscous, but rather related to a number of factors: viscosity, food particles, the complexity of the food items, their interaction, and their influence on the temporality of the in-mouth perception (Marcano, Morales, Vélez-Ruiz, & Fiszman, 2015; Morell, Ramírez-López, Vélez-Ruiz, & Fiszman, 2015; Tarrega, Marcano, & Fiszman, 2016). To further understand the relationship between sensory perception and expected satiating effects, it is required to take into account the dynamics of perception; attributes should be assessed during the length of oro-sensory exposure time. Temporal Dominance of Sensation (TDS) is a relatively new methodology in the sensory field for describing temporal perception, first presented at the Pangborn Symposium by Pineau, Cordelle, and Schlich (2003). Likewise, TDS has proven to be useful for evaluation of the dynamics of texture perceptions during food consumption (Lenfant, Loret, Pineau, Hartmann, & Martin, 2009; Saint-Eve et al., 2011). Traditionally, TDS results have been presented as average dominance curves, showing the proportion of attributes dominance against time (Pineau et al., 2009). TDS scores can be also calculated in order to compare with sensory profiling results (Labbe et al., 2009). For each sample, TDS scores are applied for different time intervals during the mastication to obtain a sample trajectory which shows the evolution of sensory perceptions when the sample is consumed (Lenfant et al., 2009). The number and duration of time intervals are fixed, and chosen based on TDS curves (Dinnella, Masi, Naes, & Monteleone, 2013).

This study aimed at exploring the role of texture of solid foods in consumers' perception and expectations of satiation and satiety, in particular the role of dynamic perception during oral processing, with barley bread as a case study.

Table 1
Bread recipes.

Ingredient	With sourdough (g)	Without sourdough (g)
Wheat flour	1300	1400
Barley	600	600
Salt	30	30
Active yeast	20	20
Water for soaking or scalding	1000	1000
Water	400	500
Sourdough	200	–

2. Materials and methods

2.1. Samples

Eight barley bread samples were manufactured at Nofima's pilot bakery, using the same formulation and ingredients but manipulating the texture of the final products by changing process parameters. Samples were equi-caloric breads, prepared from standard recipes; texture was manipulated by scalding or soaking the barley, and through fermentation, as sourdough was added to some of the batches (Table 1).

In order to investigate different texture profiles, eight breads were made, based on four factors: barley type (flour or flakes), size (fine/thin or coarse/thick), treatment (soaking or scalding) and fermentation (yes or no) (Table 2). For each type of bread, six loaves were made.

For the fermented samples, 100 g of water and 100 g of wheat flour were removed from the standard recipe, and 200 g sourdough was added (see recipes in Table 1). The sourdough, 0.15 g Florapan L73, 500 g wheat flour and 500 ml water, was fermented at 25 °C (60% RH) overnight. Depending on soaking or scalding, the barley flour or flakes were soaked in 1000 ml of water (12 °C) for one hour, or 1000 ml of water (100 °C) was added, and cooled down overnight at room temperature, respectively. During both soaking and scalding the mixture was covered with a plastic film to prevent drying. Doughs were mixed and breads baked in an industrial oven. The loaves were cooled down on a tray, and stood overnight uncovered. The loaves were sliced in a bread slicer, the ends of the loaves were discarded, and the slices from the middle part of the loaves (1.1 cm thick) were used for testing. The sliced breads were frozen, then thawed for each of the tests. Thawing was done in the same conditions for all tests.

2.2. Temporal Dominance of Sensations (TDS)

Ten assessors with previous experience in quantitative analysis and TDS took part in this study. The evaluation was conducted following the TDS approach presented in (Agudelo, Varela, & Fiszman, 2015). The assessors were firstly reminded the concept of dominant sensation at a given time during the food consumption, then tasted eight samples and listed all the dominant attributes they perceived. After that, the most frequently cited attributes were selected upon agreement among the panelists. The sensory lexicon generated for breads included eight texture attributes (Table 3) and definitions from ISO 5492:2008.

Table 2
Experimental design for baking process.

Sample	Type	Size	Treatment	Fermentation
Bread1	Flour	Fine/thin	Soaking	No
Bread2	Flakes	Fine/thin	Scalding	No
Bread3	Flour	Fine/thin	Scalding	Yes
Bread4	Flakes	Coarse/thick	Scalding	Yes
Bread5	Flour	Coarse/thick	Scalding	No
Bread6	Flakes	Fine/thin	Soaking	Yes
Bread7	Flour	Coarse/thick	Soaking	No
Bread8	Flakes	Coarse/thick	Soaking	Yes

Table 3
Texture attributes for the breads in the TDS test.

Terms	Definitions
Chewy	mechanical textural attribute related to the amount of work required to masticate a solid product into a state ready for swallowing
Coarse	geometrical textural attribute relating to the perception of the size, shape and amount of particles in a product
Crumbly	mechanical textural attribute related to cohesiveness and hardness and to the force necessary to break a product into crumbs or pieces
Dough-like	describes a solid or semi-solid product containing small, even cells filled with gas (usually carbon dioxide or air) and usually surrounded by soft cell walls
Dry	surface textural attribute that describes the perception of water absorbed by or released from a product (surface attributes)
Juicy	surface textural attribute that describes the perception of water absorbed by or released from a product (body attributes)
Soft	mechanical textural attribute relating to the force required to achieve a given deformation, penetration, or breakage of a product
Sticky	mechanical textural attribute relating to the force required to remove material that sticks to the mouth or to a substrate

For the formal assessment, assessors were first served a warm-up sample, and then tasted the samples, served simultaneously in small plastic cups coded with 3-digit random numbers. The test was conducted in individual booths under white light with adequate ventilation. Assessors were asked to put the sample in their mouth and press "START", subsequently selecting the dominant sensations while eating by clicking at all times one among eight attributes presented on the computer screen. When the sample was ready to swallow, they pressed "STOP" and spat out the sample. The assessors could successively select as many attributes as they wanted during the oral processing of the samples, including re-selecting an attribute more than once during the test. At all times, only one attribute was selected (the dominant one). Assessors were asked to rinse their mouth with water between samples.

2.3. Sample selection for quantitative descriptive analysis (QDA) and consumer testing

Based on the results from TDS analysis, four breads (Bread 3, Bread 5, Bread 6 and Bread 7, see Table 2) were chosen for QDA and consumer testing. These breads were selected on the criteria that they were the most different ones in term of dynamic texture profiles (see section 3.1.1). All tests were run November–January 2015–2016.

2.4. Quantitative descriptive analysis (QDA)

Sensory profiling was performed on four selected breads through quantitative descriptive analysis QDA (Stone & Sidel, 2004) by Nofima's trained panel. The descriptive terminology of the products was created in a pre-trial session using Breads 6 and 7. After pre-trial session lasted 1 h, the descriptors (attributes), definitions, and reference samples were agreed upon by the assessors. By the end of pre-trial, all assessors were able to discriminate among samples, exhibited repeatability during trials, and reached agreement with other members of the group. The final list was comprised of eight flavor attributes (*bitter*, *cloying*, *grainy*, *raw*, *salty*, *sour*, *sweet* and *yeast*) and eight textural attributes (*chewy*, *dough-like*, *crumbly*, *porous*, *coarse*, *hard*, *juicy* and *sticky*).

The QDA was conducted in individual booths. Two pieces of a sample were served in plastic cups coded with 3-digit random numbers, at room temperature, and in a sequential monadic manner following a balanced presentation order. The evaluation was done in two replicates and lasted 1.5 h.

2.5. Consumer test

Ninety-six consumers were recruited for the test in the southeast area of Oslo from Nofima's consumer database (51 males and 45 females, aged between 18 and 40 years). Their recruitment was based on the following criteria: consumption of coarse bread at least 2–3 days a week, not on a special diet, and neither celiac, gluten sensitive or aversive to wheat/barley. Consumers were instructed not to eat for at least 2 h and not to use products of persistent flavours at least 30 min before testing.

The formal assessment was performed in individual booths. Consumers took maximum 30 min to complete the test. At the beginning of the tasting session, the consumers were asked to rate their current level of hunger on a 100-mm line scale, ranging from "Not hungry at all" to "Very hungry". The products labeled with 3-digit codes were presented according to a sequential monadic order to balance out carry-over effects in the global data set. For each product, consumers rated their liking, satiety expectations, and answered a CATA (check all that apply) question, as follows:

Acceptance rating: "How much do you like this bread?", rated on a 9-point hedonic scale

Expected satiation: "How full do you think you would get eating this bread?" rated on a 9-point scale (1 = not at all; 9 = extremely)

Expected satiety: "For how long do you think you would feel full from this bread?", rated on a 6-point scale from 1 = "hungry again at once" to 6 = "full for five hours or longer".

CATA question: "Choose all the attributes/terms that apply to this bread". The CATA question included a list of 23 hedonic and descriptive sensory attributes (*good flavor, bad flavor, bitter flavor, grain/cereal flavor, sour flavor, taste of sourdough, yeast flavor, not coarse, medium coarse, very coarse; airy, chewy, compact, crumbly, doughy, soft, hard, heavy, juicy, dry, porous, sticky*) and 15 usage & attitude terms (*appealing, fibrous, health/nutritious, not appealing, satiating, suitable for breakfast, suitable for lunch, suitable for lunch pack, suitable for dinner, suitable for supper, unhealthy, "everyday" bread, weekend bread, would buy, would not buy*). The order of terms was randomized within the two groups (sensory and usage), between products, and across assessors.

2.6. Data analysis

The TDS data were collected with EyeQuestion (Logic8 BV, The Netherlands) and presented as TDS curves with standardized times (from T0 to T100). Briefly, there are two main lines that assist the interpretation of dominance curves in a TDS plot, "chance level", with value P_0: the dominance rate that an attribute can obtain by chance, and "significance level", with value P_s: the minimum dominance rate to be reached for the attribute occurrence to be considered as significantly higher than chance level P_0 (Pineau et al., 2009). In this study, standardized evaluation times (from T0 to T100) were split into smaller time periods with three intervals (T0–T40: beginning; T41–T80: middle; T81–T100: end) for analyzing the TDS scores (Dinnella et al., 2013). TDS scores, for each time interval, were then defined according to Eq. (1) (Labbe et al., 2009)

$$SCORE = \left(\sum_{Scoring} Proportion \times Duration\right) / \sum_{Scoring} Duration \quad (1)$$

Multiple Factor Analysis (MFA) was applied to the TDS scores. Scores and loadings were plotted from the first two components to assess sample differences and/or similarities in sensory attributes with corresponding time intervals.

A Principle Component Analysis (PCA) based on standardized data was performed to show sample trajectories in the sensory space over the mastication duration. The variables were sensory attributes, whereas the objects were samples at different time intervals (T10–T100). In the

PCA map, each trajectory was displayed by linking the ten points of time intervals corresponding to the same sample (Lenfant et al., 2009).

For QDA data, the estimated means were calculated for each of the sensory attributes using a General Linear Model with sample as a fixed effect, and a random subject effect. Differences between the attributes were assessed by ANOVA and a summary plot of all sensory differences was prepared to account for differences between samples.

Liking scores that differed between the breads were compared using one-way ANOVA with Tukey's post hoc test. Segments of consumers were identified using Hierarchical Clustering Analysis (HAC; Euclidean distance, Complete-linkage criterion).

Cochran's Q test was carried out on the CATA results in order to identify significant differences between samples for each of the attributes. Penalty-lift analysis was also performed on consumer responses to determine the effects of the presence and absence of CATA attributes on expected satiation and satiety (Williams, Carr, & Popper, 2011).

All analyses were carried out using XLSTAT, Version 2016 (Addinsoft).

3. Results

3.1. Sensory profiling with the trained panel

3.1.1. Dynamic texture perceptions via TDS

The TDS curves were obtained by plotting the dominance rate of each of the evaluated attributes across the panel for the different points of the eating period (Pineau et al., 2009). Since the duration of the consumption of the breads up to swallowing differed from one assessor to another (total evaluation time), the time scales also differed (Lenfant et al., 2009). In order to take this into account, the data from each assessor was normalized according to the individual mastication durations, such that the first scoring would be at T = 0 and the last scoring would be at T = 100. As a result of the normalization, the X-axis of the TDS curves corresponds to the normalized time (% of consumption time, from T0–T100) and the Y-axis to the dominance rate or frequency of selection of that attribute at a particular point in time (%).

Fig. 1 shows the smoothed TDS curves for the four breads showing the most distinctive temporal profiles. The other four TDS plots considered for sample selection are not presented here, interested readers should contact the authors for more info. For these four breads, TDS curves were very different both in frequency and sequence of attributes for all the breads, as per the objective of the sample selection. It was evident that texture attributes dominance rates significantly changed with the varying processing parameters. For Bread 3 and Bread 5, the attribute *chewy* was perceived as dominant during the first part of the consumption (T0–T20), and *sticky* was dominant during the end of the oral processing (T80–T100). In contrast, the dominant attributes characterizing Bread 6 and Bread 7 were *dry* in the beginning of the consumption (T0–T30) and *juicy* in the end (T80–T100). It is noteworthy that the differences between the four samples were maximized in the middle of the oral processing period. Thus, Bread 3 presented a high dominance rate value for *Dough-like* between T30 and T80, while Bread 5 was first *soft* and then *juicy* in this period. *Soft* and *Juicy* were also significant for bread 3, but was predominantly *dough-like* in the middle period; conversely, this attribute barely surpassed the significance level in Bread 5. Similarly, Breads 6 and 7 had comparable dynamic profiles in the beginning and end of the mastication, but were considerably different in the middle. In Bread 6, only *crumbly* was significantly dominant from T30 to T80, while Bread 7 was described as dominantly *chewy* and *coarse* from T20 to almost T80, when *sticky* and *juicy* became dominant (Fig. 1).

3.1.2. Static descriptive analysis of bread texture via QDA

QDA was run in eight flavor and three texture attributes. Main differences among the four samples were on the textural profile. Regarding flavor, there were minor perceptual differences in saltiness and sourness. This is consistent with the recipes and experimental design (Tables 1 and 2) which varied process parameters but kept the ingredients constant.

Fig. 2 shows the averages for all the textural attributes in the QDA test, as highlighted by the ANOVA and Tukey tests. All the attributes help discriminating among the samples. Bread 7 was the most distinct sample, significantly more *porous, hard, coarse* and *chewy* than all the other samples. Bread 3 was very similar to Bread 5 from a static point of view, with no significant differences in any of the textural attributes. They were described as low in *porosity*, *coarseness*, *chewiness* and *crumbliness* and high in *stickiness*, *juiciness* and *doughiness*. Bread 6 and Bread 7 were not significantly different in four out of eight attributes: *juicy*, *sticky*, *crumbly* and *doughy*.

3.2. Overall liking, expectations of satiation and satiety

Table 4 shows the average results for the overall population participating in the consumer test: liking and expectations of satiation and satiety. ANOVA did not show significant differences in overall liking between the four products. This indicates that consumers on average did not like any of the products more than the others. In terms of expected satiation, Bread 6 was the bread rated as to be the least satiating, whereas the difference was not significant among Bread 3, Bread 5 and Bread 7. Expectation of satiety followed a similar trend, but with Bread 7 middle way between the two groups; expected satiety scores for Bread 6 and Bread 7 (3.1 and 3.4, respectively) were generally lower than those of Bread 3 and Bread 5 (from 3.6 to 3.7). In the present study, the fact that consumers on average did not favor one sample over the others makes it easier to conclude about satiety and satiation expectations based on the textural changes and the dynamics of perception. It is necessary, however, to look into the liking into more details to see if there were groups of consumers with different liking patterns and if so, different satiety expectations patterns from the total consumer sample.

When Cluster Analysis was applied to preference data, three segments of consumers were initially detected, including cluster 1 (n = 60), cluster 2 (n = 29) and cluster 3 (n = 7). The focus here will be on clusters 1 and 2, as the third is too small to conclude on. Cluster 1 did not present significant differences between bread samples in product overall liking ratings (p-value = 0.427).

In cluster 2, significant differences in hedonic score were detected among products (p-value = 2.8e − 4). Bread 7 was considered as the best liked (average score = 5.0), followed by Bread 6, Bread 5 and Bread 3 with no significant differences between these last three. In general, trends in this cluster did not differ much from the total consumer sample in terms of satiety and satiation expectations, these consumers just discriminated less in general. However, for these 29 consumers like for the total sample, Bread 6 was still the one rated as less satiating based on their expectations.

3.3. Texture perception, oral processing, and consumers' expectations of satiety and satiation

As per the previous sections, results showed that the formulated bread samples, with no differences in ingredients, composition and caloric content, and no large differences in acceptability levels, have been perceived by consumers as different in expected satiety and satiation. The hypothesis is that the main differences driving this perception are based on the oral processing and the perceptual textural differences during the eating of the samples. In the next two sections, the focus will be on the understanding of those differences, based on the dynamic perception as assessed by the trained panel (TDS) and the consumers' perception of the products as per the CATA results.

3.3.1. Role of dynamics of perception in the expectations of satiety and satiation

In order to gain further understanding of the dynamics of

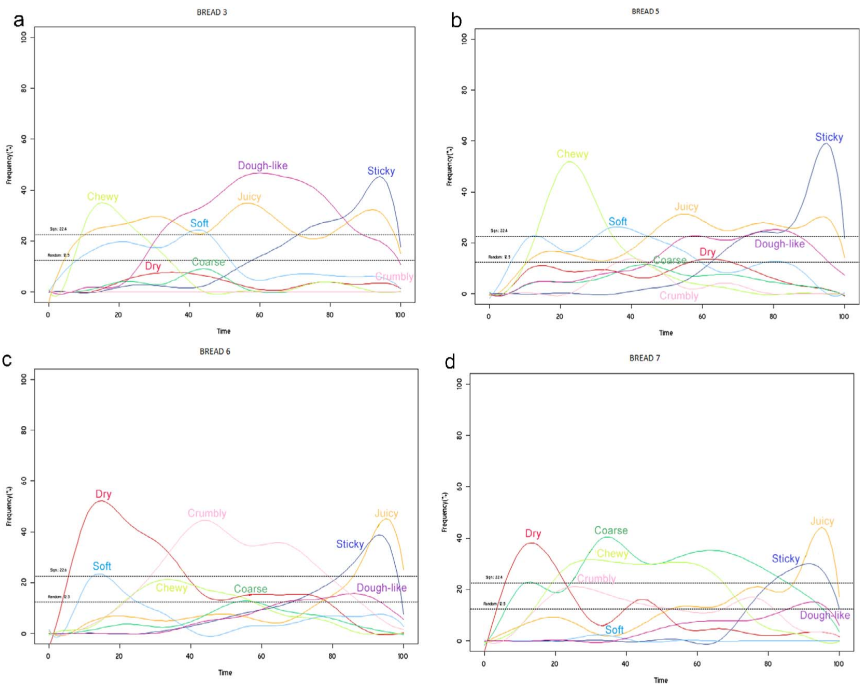

Fig. 1. TDS plots for Bread 3 (a), Bread 5 (b), Bread 6 (c) and Bread 7 (d).

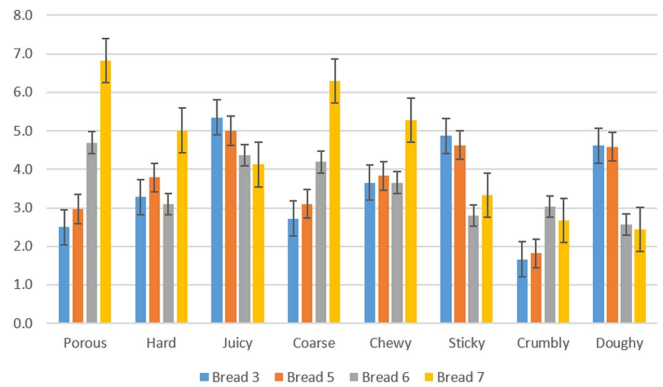

Fig. 2. Average intensities of the textural attributes in the QDA.

Table 4
Effect of product on overall liking, expectations of satiation and satiety.

	Liking	Expected satiation	Expected satiety
Bread3	5.1[a]	5.8[a]	3.6[a]
Bread5	5.1[a]	5.8[a]	3.7[a]
Bread6	5.0[a]	4.6[b]	3.1[b]
Bread7	5.5[a]	5.3[a]	3.4[ab]

Different letters in the same column indicate statistical differences ($p < 0.05$) among the products.

perception, TDS standardized time was split into three intervals of the oral processing period (*beginning*, *middle* and *end*). The number and duration of time intervals did not affect the relative differences among products (Dinnella et al., 2013). The interval sizes have to be short enough to glean temporal information and large enough to capture what the panel as a whole perceived over the bread. Therefore, based on the observation of the TDS plots, T0–T40, T41–T80 and T81–T100 were selected for the beginning, middle and end intervals, respectively.

MFA was applied on the time intervals data of the TDS, in order to study the relationships between the samples and the temporal dynamic attributes during the three stages of the mastication, and to being able to plot them together with the consumers' expected satiety and expected satiation results (Fig. 4). The first dimension opposed products in terms of *dough-like* dominance perception (from beginning to end of consumption), juiciness at the beginning and middle (*b.juicy, m.juicy),* and stickiness perception in the middle of the eating period (*m.sticky*). Breads 3, 5 and Breads 6, 7 were located on the right and left extremes

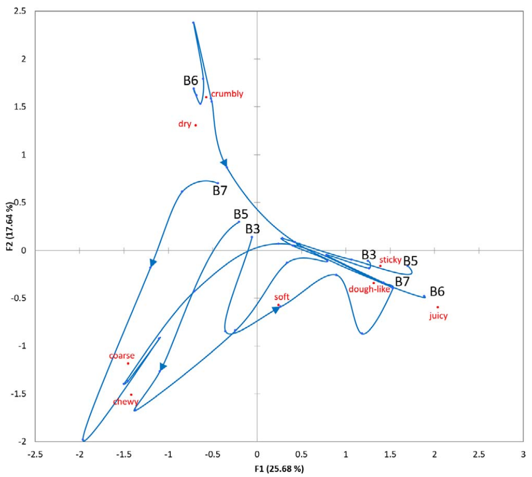

Fig. 3. TDS trajectories. (B3, B5, B6 and B7 are Bread 3, Bread 5, Bread 6 and Bread 7, respectively).

of the plot, respectively. Bread 5 and Bread 3 were grouped very close together in the MFA perceptual map, described as dominantly *dough-like* from beginning to end of the consumption, dominantly *juicy* and *sticky* in the *middle, and soft* in the *beginning.*

Bread 6 was characterized by being dominantly *crumbly* (both in the beginning and middle), and *dry* in the beginning, whereas Bread 7 presented high dominance rates for *coarse* (during the whole consumption) and *m.chewy* (dimension 2). However, both breads were perceived *dry* in the beginning and *juicy* in the end of consumption (dimension 1).

In the correlation map (plot on the right in Fig. 4), expected satiation and expected satiety were plotted as supplementary attributes. The results indicated that the expectations were driven by *chewy* dominance (mainly in the beginning of consumption, but also partially during the rest of the mastication) and negatively correlated to *crumbly (*beginning and middle*)*, *b.dry* and *e.juicy*. *Chewiness* and *coarseness* dominance differentiated bread 7 from bread 6, which was expected to be less satiating. A more satiating barley bread would then be either dominantly *coarse* throughout the mastication and *chewy* in the middle stages, or else dominantly *chewy*, *sticky* and *dough-like* throughout the mastication; on the contrary, a barley bread which is not perceived as *chewy* is dominantly *crumbly* in the first stages of the mastication and is *dry* in the beginning, will be perceived as less satiating. *Juiciness* might be a driver of higher expectations of satiety in the beginning and end of the eating period, but not in the end.

Table 5
Cochran's Q test for each attribute for the four breads.

Attributes	p-values	Bread3	Bread5	Bread6	Bread7
Compact	0.000	0.69[b]	0.67[b]	0.15[a]	0.17[a]
Crumbly	0.004	0.06[a]	0.13[ab]	0.23[b]	0.13[ab]
Doughy	0.000	0.43[b]	0.39[b]	0.20[a]	0.20[a]
Dry	*0.065*	*0.29[ab]*	*0.33[ab]*	*0.40[b]*	*0.23[a]*
Heavy	0.000	0.43[b]	0.38[b]	0.03[a]	0.15[a]
Juicy	*0.436*	0.29[a]	0.27[a]	0.20[a]	0.26[a]
Soft	*0.120*	0.38[a]	0.37[a]	0.46[a]	0.31[a]
Porous	0.000	0.05[a]	0.09[a]	0.25[b]	0.26[b]
Sticky	0.000	0.45[b]	0.35[b]	0.18[a]	0.29[ab]
Chewy	*0.066*	*0.23[a]*	*0.23[a]*	*0.10[a]*	*0.19[a]*
Hard	0.042	0.07[a]	0.07[a]	0.01[a]	0.02[a]
Aery/fluffy	0.000	0.09[a]	0.15[a]	0.63[b]	0.64[b]
Not coarse	0.000	0.21[a]	0.25[ab]	0.40[b]	0.12[a]
Coarse	0.003	0.41[a]	0.48[ab]	0.37[a]	0.60[b]

Same letters mean no significant differences between samples according to Marascuilo test.

3.3.2. CATA question. Drivers of expected satiation and satiety

Of the 14 texture attributes listed in the CATA questionnaire (*medium coarse* and *very coarse* were considered *coarse*), Cochran's Q test (Table 5) showed that 10 of the attributes presented significant differences between the samples (all except for *dry, juicy*, *soft* and *chewy*).

The Correspondence Analysis result displays the differences and similarities between the products in a bi-dimensional space (Fig. 5). The first dimension (87% of total variability) separated products into two groups, particularly, group 1 (Bread 3 and Bread 5) was located on the left, group 2 (Bread 6 and Bread 7) on the right. This position was in line with the product discrimination based on TDS results (Fig. 4). Bread 3 and Bread 5 were perceived as *doughy*, *compact*, *hard* and *heavy*. Breads 6 and 7 were positioned on opposite sides of the second dimension (12% of total variability). On the negative side of dimension 2, Bread 7 was considered as *coarse* and *porous*, *aery/fluffy*. Bread 6, on the positive side of dimension 2, was particularly described as being

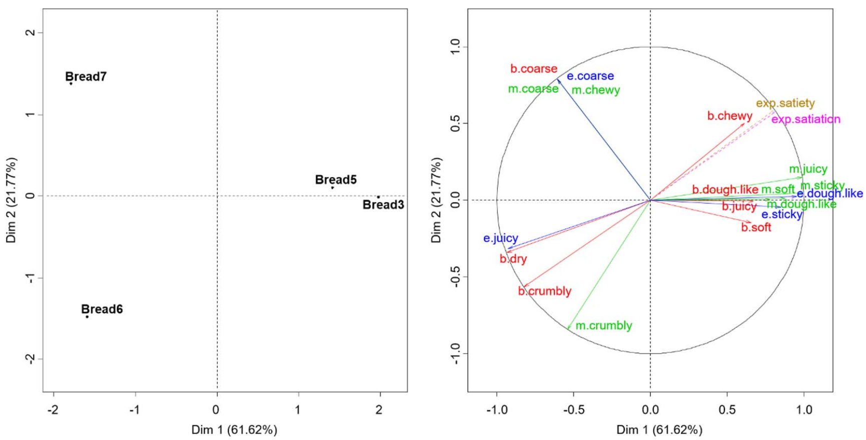

Fig. 4. Representation of the bread samples (*left*) and the dynamic sensory attributes (TDS data, *right*) across all oral processing intervals on the first two dimensions of the MFA. (*b.*, *m.* and *e.* were the notation of beginning, middle and end time intervals; expected satiety and satiation were plotted as supplementary variables).

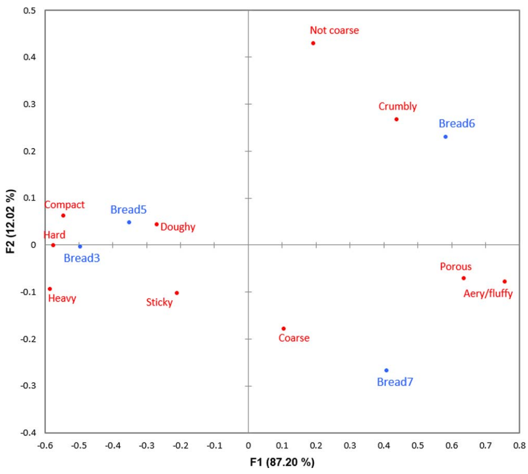

Fig. 5. Representation of the CATA texture attributes and products (Correspondence Analysis).

crumbly, *not coarse, porous* and *aery/fluffy*. Note that product Bread 6 was the one expected to be the least satiating (Table 4), suggesting the attributes *crumbly* and *not coarse* would be negative drivers for the expectations of satiety in this sample set, in agreement with the findings on the temporal data reported in Section 3.3.1. Bread 7 was also perceived as *porous* and *fluffy* by consumers, but *coarseness* has driven the expectations of satiety in this sample. This is in line with the results obtained with the TDS data and indicates that a high *coarseness* could be a driver of enhanced satiety expectation.

In order to examine the impact of different attributes on satiation and satiety, a penalty-lift analysis was performed based on the CATA data, to determine the effects in the expectations of satiating effects with the presence and absence of CATA attributes. This approach has been used in the past to study the effects on liking scores of checked and non-checked attributes (Ares, Dauber, Fernández, Giménez, & Varela, 2014; Meyners, Castura, & Carr, 2013), and to relate CATA answers to expectations of satiating capacity (Tarrega et al., 2016). In the present study, satiety (or satiation) 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. Calculating the differences between those averages one can estimate the change in satiety expectations (or satiation) due to this attribute being checked versus not checked in the CATA questions.

Fig. 6 shows the results of the penalty-lift analysis, indicating the attributes that had positive or negative impacts on the expectations of satiation and satiety.

Compact, *coarse* (merged from *medium coarse* and *very coarse*) and *heavy* were found to be the most important drivers of expectations of satiety and satiation, as highlighted by the attributes evaluated in the CATA question. They increased the expected satiation by almost up to 1 point on the 9-point scale, and satiety expectations up to 0.5 point on the 6-point scale when checked, as compared to being not checked. The results also reveal that *aery/fluffy* and *not coarse* were inhibitors of expected satiation and expected satiety by suppressing the expectations about 1 point and 0.5 point, respectively. These results are in agreement with some of the findings from the dynamic perception evaluated via TDS. *Chewy* and *doughy*, that were suggested as important drivers of the expectations by the TDS results, were not highlighted by the penalty-lift as drivers of consumer perception. However, looking into the CATA count table one could see that consumers perceived these attributes as less associated to Bread 6, which is consistent with these results. Further research should relate to the information about an ideal product, including sensory, consumer preferences, expectations of satiation and satiety; the evaluation of an ideal satiating bread could enable the identification of what underlies consumer perceptions in a further detail.

4. Discussion

4.1. Static vs. dynamic descriptive profiles

Compared to QDA results (Fig. 2), the individual TDS plots (Fig. 1) and the product trajectories defined by the temporal data (Fig. 3) highlight some interesting key differences that allowed a better discrimination among the four samples under study. QDA scores are only an integration of all the changes that have occurred during the mastication process, not pointing out the dynamic aspects of in mouth texture perception, as highlighted by (Lenfant et al., 2009) when proposing the concept of sensory trajectory. Taking for example Bread 6 and Bread 7, they were described as very similar in static profiles but not quite similar from a dynamic point of view, as per the observation of their TDS plots, both were perceived as *dry* at the beginning and *juicy* and *sticky* at the end, but the perception in the middle period of the oral processing was characterized by different dominant attributes. For Bread 6, *crumbly* was dominating during the middle of consumption. By contrast, *coarse* and *chewy* were dominant for Bread 7. These differences were also highlighted by the product trajectory plot, where both samples start as *dry* and move in the perceptual space towards different directions, to then "meet again" in the *sticky, juicy* region of the plot.

In addition, some attributes were also described very differently between QDA and TDS approaches. *Juicy*, for example, presented very

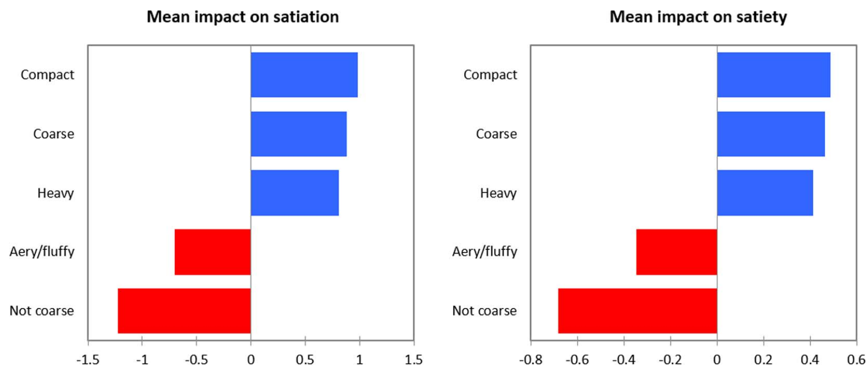

Fig. 6. Penalty-lift analysis of expected satiation (left) and expected satiety (right).

similar intensity ratings for the four samples in the QDA; however, the individual TDS plots showed that *juiciness* was dominant at different points of the mastication, for Breads 3 and 5 it dominated in the middle of the eating period and remained significant until the end, while for Breads 6 and 7 it only became significant and dominant at the end. Looking at the trajectory plot, all products followed a distinct path, and "met" at the end of the oral processing in the *juicy* and somehow *sticky* and *doughy* area. One explanation for this is that all products in mouth need to be diluted and comminuted until a "swallowing threshold" is reached (Witt & Stokes, 2015). In this case, *juicy* might be the attribute which was the signal for readiness to swallow, such as all products were perceived the same way at the end of consumption. For *chewy*, QDA results indicated that Bread 7 was rated the most intense, significantly different from Bread 3, Bread 5 and Bread 6. Nevertheless, Bread 7 was not particularly high in *chewy* dominance throughout its eating period, while Breads 3 and 5 showed dominance peaks at the beginning of the consumption for this attribute. Specifically, while *chewy* was strongly linked to Bread 3 and Bread 5 at the beginning, it only linked to Bread 7 at the middle of consumption, as highlighted in the trajectory plot. This implies that the product discrimination based on static profiles might not figure out the actual textural differences as perceived throughout the eating experience. Due to the dynamic nature of sensory perceptions, TDS, rather than QDA method, seemed to get a more detailed description of the actual textural differences between the products.

4.2. Expectations of satiety, satiation and liking

The results show the differences in evaluation between expectations of satiation and satiety. This might be due to the nature of each concept, satiation was mostly influenced by sensory attributes, whereas satiety was not only correlated to sensory but also cognitive, post-ingestive and post-absorbative (Blundell et al., 2010) so it could be more difficult to measure it based on expectations only. Furthermore, the difference in scaling might have influenced, as expected satiety was measured in a 6-point scale, with less discriminating capacity than the 9-point used for measuring expected satiation. Liking is also very much correlated to expected satiety and portion size determination (Blundell et al., 2010). Liking and pleasure, linked to sensory specific satiety, might be what guide humans to eat balanced, varied meals in macronutrient and micronutrients without nutritional knowledge, however liking only does not predict when a meal ends (Møller, 2015).

4.3. Oral processing and expectations of satiety and satiation

In a previous work, Tarrega et al. (2016) found that attributes associated to oral processing, *sticky* and *chewy*, were not influential on expectations of satiation and satiety for yogurts with pieces, but semi-solid and solid samples could be perceived differently in terms of satiating effects, as liquids do not necessarily elicit the same brain responses as solids with regards to oral stimuli (Tarrega et al., 2016; Teff, 2010).

Ferriday et al. (2016) found that unmodified meals consumed to a fixed portion with variations in oral processing (fast/slow) affected fullness, so the modification of the oral process could also impact meal size. These authors suggested modifying food form to encourage increased oral processing that help to nudge consumers to manage their food consumption. Results from Morell et al. (2014) indicated the same, as they found that creaminess at the beginning of the consumption of smoothies with different thickeners, influenced satiety expectations.

In this study, results show that in solid foods like barley breads with the same ingredients, same composition and same caloric content, the oral processing, determined by textural changes, is the driver of different expectations of satiety and satiation. This has direct practical implications, and suggests clear directions for potential process changes to increase satiety perception in the case under study (barley bread). In addition, expectations of satiation and satiety were perceived differently although liking was similar for all breads. This supports the hypothesis that the expectations were mostly determined by the dynamic sensory perception of texture.

5. Conclusions

This paper aimed at understanding consumers' satiety expectations on barley breads in light of their temporal texture profiles. Results showed that in solid foods like barley breads, with the same composition (same ingredients) and same caloric content, the oral processing, as determined by textural changes, was an important driver of different expectations of satiety and satiation.

Temporal Dominance of sensations (TDS) proved useful for highlighting product discrimination of similar corresponding descriptive properties in this sample set. *Chewiness* dominance, mainly in the first stages of mastication, and *coarseness* throughout the mastication were drivers of enhanced satiety perceptions, whereas a dominant perception of *dryness* and *crumbliness* at the beginning were linked to breads less expected to be satiating.

The penalty lift analysis on the CATA results highlighted *compact*, *coarse* and *heavy* as the most important drivers of expectations of satiety and satiation for consumers, while *aery/fluffy* and *not coarse* were inhibitors of those perceptions.

From a practical perspective, *compact*, *coarse* and *heavy* might be the most advisable properties to pursue for obtaining an enhanced expectation of satiation and satiety in barley breads.

In general, more research will be needed to generalize these findings for other solid and semi-solid products; nevertheless, the management of texture looks as a promising way to modify product properties and create more satiating foods that could reduce food intake, in a world where obesity is a huge concern.

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PAPER 2

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When the choice of the temporal method does make a difference: TCATA, TDS and TDS by modality for characterizing semi-solid foods

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ABSTRACT

For describing the evolution of sensory properties during eating, dynamic sensory methods are still being developed and optimised. Temporal Dominance of Sensations (TDS) and Temporal Check All That Apply (TCATA) are currently the most used and discussed. The aim of this study was to compare TDS, TCATA and a variant of TDS, performed by modality (M-TDS) in the outcome of the dynamic sensory description. These methods were applied with the same trained panel (n = 10) for the evaluation of the dynamic properties of yoghurt samples, with identical composition, only varying in textural properties. Based on a design of experiment, the yoghurts varied in viscosity (thin/thick), size of cereal particle added (flour/flakes) and flavour intensity (low dose/optimised dose, by adding artificial sweetener and vanilla).

The TDS curves revealed that the variation in viscosity and particle size led to differences in perception mainly at the beginning of the eating process (*Thin/Thick* and *Gritty/Sandy*). Additionally, all samples were also perceived as *Bitter* at the end of the eating process. TCATA and TDS by modality results were, generally, in agreement with TDS, but they unveiled more details of the samples' dynamic profiles in all stages of the eating process, showing the effect of *Vanilla* and *Sweet* for the samples with optimised flavour, and the masked perception of *Bitter*.

The duration of the eating process was standardized and split into three time intervals (T0-T40, T41-T80, T81-T100). Panelists' responses were summarized as frequency values in each time interval. Principal Component Analysis was used to visualize sample trajectories over time in the sensory space, with the need to study up to the third dimension to better understand the trajectories. ANOVA models were used to find the attributes which were significantly differences among products. Panel performance was assessed based on MANOVA models for the three methods. The results indicated that TCATA was more discriminative and panelists were more in agreement. TCATA also described samples in more detail in terms of number of discriminating attributes as compared with TDS. The discussion also centers in the different aspects of perception that could respond to different research questions for the three compared methods.

1. Introduction

Eating facilitates two very basic functions for human beings: to gain energy and nutrition and to gain pleasure and enjoyment; understanding sensory perception is essential to explain people's eating behaviour, consumers' acceptance and linking of food products (Chen, 2015; Koc, Vinyard, Essick, & Foegeding, 2013). Processes involved in eating, e.g. mastication and salivation, are dynamic processes (Dijksterhuis & Piggott, 2000). Some models have been proposed to explain the breakdown pathway of food during oral processing that emphasized the dynamic and complex nature of sensory perceptions during the continuous transformation of food from first bite to swallowing (Hutchings & Lillford, 1988; Koc et al., 2013). These researches indicate that sensory perception is a dynamic phenomenon, that is, perception of aroma, taste and texture in foods is dynamic perceptual process with the intensity of attributes changing throughout the steps of oral processing (Cliff & Heymann, 1993).

Descriptive sensory techniques are designed to provide a measure of sensory perceptions based on human assessments relying on methods from neurophysiology and psychology. In sensory analysis, various methods can be used to gain a better understanding of what sensory attributes are responsible for the perceived quality of the products.

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Classically, sensory methods have focused on static judgements, measuring the averaged intensities of sensations instead of time course of sensations (Di Monaco, Su, Masi, & Cavella, 2014). These methods for sensory profiling do not consider the temporal aspects of sensory perception and may miss crucial information for understanding consumer preferences (Lawless & Heymann, 2010c). This necessitates the study of the methods for measuring dynamics of sensory perception.

Several temporal sensory methods have been developed for dynamic sensory characterization (Cadena, Vidal, Ares, & Varela, 2014). Time Intensity (TI) consists in recording the evolution of the intensity of a given sensory attribute over time. Although the concept of TI was early approached in 1937 (Holway & Hurvich, 1937), this method was used quite extensively since 1970s (Lee & Pangborn, 1986). Nevertheless, TI methodology is performed only on a small number of attributes or with a limited number of products since only one attribute was evaluated at a time (Pineau et al., 2009). In TI, shapes of TI curve are more subject than product dependent (Sudre, Pineau, Loret, & Martin, 2012), leading to individual curves are considered individual "signatures" of assessors; therefore, it is difficult to get the general results for all assessors.

To cover more attributes, TI was extended to the Dual Attribute Time Intensity (Duizer, Bloom, & Findlay, 1997), the Modified Time Intensity (Pionnier et al., 2004) and later on Temporal Dominance of Sensations (TDS). TDS was developed as of 1999 at the "Centre Européen des Sciences du Goût" in the LIRIS lab and first presented at the Pangborn Symposium by (Pineau, Cordelle, & Schlich, 2003). In its inception, TDS was based on Ep Kõster's idea of a "harmonium of sensations"; he imagined it like a piano "where the panelist could play the melody of the product", with each piano key as a sensory attribute; this complexity was simplified in TDS to "one key at a time" (Schlich & Pineau, 2017). This method consists in presenting to the assessors a list of attributes, the assessors are then asked to assess which of the attributes is perceived as dominant. During the course of the evaluation, when the assessor consider that the dominant attribute has changed, he or she has to select the new dominant sensation (Labbe, Schlich, Pineau, Gilbert, & Martin, 2009; Pineau et al., 2009). Results from TDS data are described as TDS curves, the dominant rates of attributes (Y-axis) against time (X-axis) for each sample (Cadena et al., 2014). When several attributes have to be compared over time, TDS would be in principle better suited; however, some aspects have been questioned. The first one is the definition of dominant attribute; a dominant attribute is defined as the attribute associated to the sensation catching the attention at a given time (Pineau et al., 2009), whereas other definition shows that dominance is the most intense sensation (Labbe et al., 2009). Apparently, consensus regarding the definition of this concept is lacking between studies (Cadena et al., 2014). In addition, this requirement for sequential selection can potentially result in loss of relevant sensory information, particularly when dealing with complex products that elicit several sensations simultaneously during consumption (Ares et al., 2015). In a recent study, (Varela et al., 2017) explored the conceptualization of "dominance" by trained assessors and consumers. They found that dominance is a complex construct related to multiple aspects of perception, and that different conceptualizations within a panel can influence the interpretation of results. Controversial issues highlighted were around how attributes are selected, the drivers of transitions between attributes, the competition of sensory modalities and how some phenomena like dumping or dithering could happen at some stages in TDS.

TCATA, the temporal extension of Check All That Apply developed in recent years, could potentially overcome some of those issues. In TCATA, the assessors' task is to indicate and continually update the attributes that apply to the sample moment to moment, that is, one or more applicable sensations are tracked at a given time during mastication (Castura, Antúnez, Giménez, & Ares, 2016). Compared with TDS, TCATA enables the evaluation of more than one attribute at each time, resulting in more detailed description of sensory characteristics of products over time (Ares et al., 2015). However, the assessors may be so focused on continuously selecting and un-selecting terms that describe a sample that it could result, in some cases, in a more complex or fatiguing method (Ares et al., 2016); this could be particularly the case in a new variant of TCATA, TCATA-Fading, in which the selected attributes become unselected over a predefined duration.

One important drawback of TDS is that dithering and dumping might be enhanced when taste and texture are evaluated in the same task, as fewer terms are available per modality and because panelists need to decide both on the modality and on the attribute (Varela et al., 2017). One possible modification which could overcome this issue, would be running TDS in separate steps, where panelists would be allowed to assess each modality in a different screen, hereby called TDS by modality or M-TDS. This latter method has been proposed by (Agudelo, Varela, & Fiszman, 2015) and applied on fruit fillings and later on cheeses (Bemfeito, Rodrigues, Silva, & Abreu, 2016), but it has not been formally compared to TDS or TCATA from a methodological standpoint.

Until now, some papers have shown that TCATA and TDS provided comparable sample information (Ares et al., 2015), whereas other suggested that TCATA and its variants were able to improve discrimination and deliver a more detailed description (Ares et al., 2017, 2016). The divergence could result from the different products evaluated, or the lack of specific criteria for comparison between the temporal methods.

In this context, the objective of present work was to compare these three temporal methods (TDS, TCATA and M-TDS) based on detailed criteria consisting of dynamic profile, product trajectory and panel performance. The discussion will also center on the different aspects of perception that could respond to different research questions for the three compared methods. This critical comparison will add to the body of literature that can help researchers to select the temporal method best suited to their needs.

2. Materials and methods

2.1. Samples

The idea behind the present research was to start from a design of experiment (DOE) based on the same ingredients, only modifying the product texture by using different processing strategies, so as the samples would have the same calories and composition and these parameters would not influence satiety or satiation, as this methodological study is part of a bigger project looking into satiety perception. The parameters of the DOE were: viscosity (thin/thick), particle size (flake/flour) and flavour intensity (low/optimal). For creating the viscosity differences, two types of yoghurts bases were prepared, one commercial natural yoghurt and another using the same yoghurt in which the texture was modified by stirring for 10 min at 25,000 rpm in an Ultraturrax PT 3100, irreversible disrupting the gelled structure of the yoghurt and obtaining a thinner, stable version. For the two particle sizes, oat was added in either flakes or flour. Oat flour was obtained by milling the oat flakes with an Ultra Centrifugal Mill ZM200 using a 0.5 mm sieve. Flavour level was varied using two different levels of a combination of acesulfame K and vanilla aroma. "Optimal flavour" intensity was the recommended by the industry providing the yoghurt as the level of sweetener and vanilla they use in commercial low sugar vanilla yoghurt. The "low flavour" level was a perceivable lower level, as per informal tasting by the research team. The optimal intensity was 0.025% acesulfame K and 0.05% vanilla, whereas low level was half of those levels. Finally, eight yoghurt samples were obtained varying in viscosity, particle size of oats and flavour intensity, as per the DOE in Table 1.

The materials used in the preparation of the yoghurt samples were commercial yoghurts (TINE Yoghurt Naturell, TINE, Norway), oat flakes (AXA 4-korn, AXA, Norway), acesulfame K and vanilla supplied by TINE, Norway.

Table 1
Formulation of the yoghurt samples.

Sample	Viscosity	Particle size	Flavour intensity
P1 (t-F-l)	Thin	Flakes	Low
P2 (T-F-l)	Thick	Flakes	Low
P3 (t-f-l)	Thin	Flour	Low
P4 (T-f-l)	Thick	Flour	Low
P5 (t-F-o)	Thin	Flakes	Optimal
P6 (T-F-o)	Thick	Flakes	Optimal
P7 (t-f-o)	Thin	Flour	Optimal
P8 (T-f-o)	Thick	Flour	Optimal

All the sensory evaluations were conducted by Nofima‘s trained panel, in standardized individual booths according to ISO standards (ISO 8589, 2007). Samples were served in plastic containers coded with 3-digit random numbers and in a sequential monadic manner following a balanced presentation order. Thirty grams of each yoghurt was served to each assessor for all the evaluations. Two replicates were run for QDA and three replicates for the temporal descriptive tests (TDS, TCATA and M-TDS). Samples were evaluated during normal consumption (no time restriction) and they were spat out after evaluation for the three methods.

2.2. Trained panel

Nofima's panel is a highly trained, very stable panel, the 10 assessors are solely hired as tasters, with a part time job, and some of them have more than 20 years' experience working with descriptive analysis. Panel performance is assessed frequently, and checked for every project. That ensures that all panelists are good enough based on three important qualities: discrimination, repeatability and agreement. The panel has 7 years' experience with TDS and one year of experience with TCATA.

2.3. Quantitative descriptive analysis

Generic quantitative descriptive analysis, inspired in QDA®, was also used in this study as a frame of reference on the static profile of the samples. Sensory profiling was performed on eight samples through generic quantitative descriptive analysis (Lawless & Heymann, 2010a; Stone, Bleibaum, & Thomas, 2012, chap. 6). The descriptive terminology of the products was created in a pre-trial session using samples 4 and 5. These samples were selected in informal tasting by the researchers and panel leader, for showing extremes examples stretching the sensory space. 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 (Table 2) was comprised of six odour attributes (*Intensity, Acidic, Vanilla, Stale, Sickening, Oxidized*), three taste attributes (*Sweet, Acidic, Bitter*), six flavour attributes (*Intensity, Sour, Vanilla, Stale, Sickening, Oxidized*) and six texture attributes (*Thick, Full, Gritty, Sandy, Dry, Astringent*).

2.4. Temporal dominance of sensations (TDS)

Trained sensory panelists ($n = 10$) were used for TDS task. The evaluation was conducted following the TDS approach presented by Pineau et al. (2003). Two preliminary sessions were conducted, in which samples were presented in monadic order. In the first, the panelists listed all dominant attributes they perceived while tasting two samples (P4, P5). They discussed these sensations before tasting three next samples (P1, P2 and P8) in the second session. After that, the most frequently cited attributes were selected upon agreement among the panelists. The sensory lexicon generated for the temporal description of the yoghurts included ten attributes (taste/flavour, texture) with their definitions (Table 3).

For the formal assessment, samples were assessed in triplicate. Assessors were asked to put a spoonful of the sample in their mouth and press “START”, subsequently selecting the dominant sensations while eating by clicking at all times one among the ten attributes presented on the computer screen. When the sample was ready to swallow, they pressed “STOP” and spat out the sample. The assessors could successively select as many attributes as they wanted during the oral processing of the samples, including re-selecting an attribute more than once during the test. At all times, only one attribute was selected (the dominant one). Assessors were asked to rinse their mouth with water between samples. Dominance was defined as the sensation that caught assessors' attention at a given time, not necessarily the most intense.

2.5. Temporal check all that apply (TCATA)

The procedure was as described by Castura, Antúnez et al. (2016), Castura, Baker, and Ross (2016). Assessors were instructed to review the attributes prior to the evaluation, to get familiar with the attribute distribution on the screen. The TCATA list included ten attributes, the same as in the TDS task. Assessors were asked to check the terms that applied to describe the sensory characteristics of samples at each moment of the evaluation and to uncheck the terms when they were no longer applicable. Unlike TDS, multiple attributes can be selected simultaneously. During the evaluation, the assessors were free to check any unselected attribute, or to uncheck any selected attribute at all times.

2.6. Temporal dominance of sensations by modality (M-TDS)

The procedure is similar to the one conducted in TDS task except for the evaluation of flavour and texture modalities in 2 different steps. The list of attributes is the same as describes on Table 3. The assessors tasted one mouthful of a sample and described the dominance of the flavour attributes (*Acidic, Bitter, Cloying, Sweet, Vanilla*) on the first screen. After this, they rinsed their mouths, tasted a second mouthful of the same sample and selected the dominance of the textural attributes during time (*Dry, Gritty, Sandy, Thick, Thin*) on a second screen. The procedure was repeated for the rest of samples.

2.7. Data analysis

2.7.1. Data in sequence of time points

Time standardization was applied to remove assessor noise (Lenfant, Loret, Pineau, Hartmann, & Martin, 2009).

For each point of time, the proportion of runs (subject*replication) for which the given attribute was assessed as dominant was computed. These proportions were smoothed and plotted against time. The curves were called TDS curves. There were two main lines that assisted the interpretation of dominance curves in a plot, “chance level” and “significant level”. The former represented the theoretical proportion of subjects selecting an attribute at random. Its value, P_0, is equal to $1/p$, p being the number of attributes. The latter represented the smallest proportion that can be declared as being significantly higher than the chance level (binomial distribution, $\alpha = 0.05$). It was calculated using Eq. (1) with n as the number of subject*replication (Pineau et al., 2009).

$$P_s = P_0 + 1.645\sqrt{\frac{P_0(1-P_0)}{n}} \tag{1}$$

For M-TDS, the two modalities – flavour and texture – were recorded on two consecutive screens. For each product and each point in time, the dominant rates by modalities were separately calculated and then plotted together. Since it is possible to obtain two dominant attributes (one for flavour, another for texture) at a given time, the sum of

Table 2
Sensory attributes for QDA task.

Attribute	Abbreviation of attribute	Definition
Intensity odour	Intensity_o	Total intensity of all odours in the product
Acidic odour	Acidic_o	Relates to a fresh, balanced odour generally due to the presence of organic acids
Vanilla odour	Vanilla_o	Relates to a vanilla odour
Stale odour	Stale_o	Relates to a stale odour (as in cloying, barn, refrigerator etc.)
Sickening odour	Sickening_o	Relates to a sickening odour (as in cloying)
Oxidized odour	Oxidized_o	Relates to an odour caused by oxidization (cardboard)
Intensity flavour	Intensity_f	Total intensity of all tastes and flavours in the product
Sour flavour	Sour_f	Relates to a fresh, balanced flavour generally due to the presence of organic acids
Sweet taste	Sweet_t	Relates to the basic taste sweet (sucrose)
Acidic taste	Acidic_t	Relates to the basic taste acid (citric acid)
Bitter taste	Bitter_t	Relates to the basic taste acid (caffeine)
Vanilla flavour	Vanilla_f	Relates to a vanilla flavor
Stale flavour	Stale_f	Relates to a stale flavour (as in cloying, barn, refrigerator etc.)
Sickening flavour	Sickening_f	Relates to a sickening flavour (as in cloying)
Oxidized flavour	Oxidized_f	Relates to a flavour caused by oxidization (cardboard)
Thick	Thick	Mechanical textural attribute relating to resistance to flow. It corresponds to the force required to draw a liquid from a spoon over the tongue
Full	Full	Mechanical textural attribute relating to resistance to flow. A rich sensation of the product in the mouth
Gritty	Gritty	Geometrical textural attribute relating to the perception of the size and shape of particles in a product
Sandy	Sandy	A sandy sensation of a sample in the mouth
Dry	Dry	Relates to a feeling of dryness in the mouth
Astringent	Astringent	Describes the complex sensation, accompanied by shrinking, drawing or puckering of the skin or mucosal surface in the mouth

Table 3
Sensory attributes for the yoghurts in the three temporal tasks.

Term	Definition
Acidic	Relates to the basic taste acid (citric acid)
Bitter	Relates to the basic taste acid (caffeine)
Cloying	Relates to a cloying flavour (stale, sickening, flavourless)
Dry	Relates to a feeling of dryness in the mouth
Gritty	Geometrical textural attribute relating to the perception of the size and shape of particles in a product
Sandy	A sandy sensation of a sample in the mouth
Sweet	Relates to the basic taste sweet (sucrose)
Thick	Mechanical textural attribute relating to resistance to flow. It corresponds to the force required to draw a liquid from a spoon over the tongue (High intensity = viscous − thick)
Thin	Mechanical textural attribute relating to resistance to flow. It corresponds to the force required to draw a liquid from a spoon over the tongue (No intensity = fluid − thin)
Vanilla	Relates to a vanilla flavour

the dominance rates for attributes of each modality, instead of all attributes, was equal to 1.

Basically, TCATA data was arranged in a matrix, with attributes in rows and time slices in columns. An evaluation was the citation proportion of each attribute, calculated as the proportion of judgments (assessors*replicates) for which it was selected for describing a sample at a given time. TCATA curves were showed as smoothed attribute citation proportions over time. For each TCATA attribute, the citation rate of a product of interest can be contrasted with the average citation rate of the other products (Castura, Antúnez et al., 2016).

Whether TDS or TCATA data, covariance Principle Component Analysis (PCA) was conducted on the table of mean citation proportions (TCATA data) or dominance rates (TDS data) with Product*Times in rows and Attributes in columns. By linking adjacent time points corresponding to the same sample, product trajectories described the evolution in how the sample was characterized over time (Castura, Baker, & Ross, 2016).

2.7.2. Aggregated data in time intervals

Without loss of generality, the evaluation duration in temporal data was split into smaller time intervals (T0-T40: beginning; T41-T80: middle; T81-T100: end) as presented in several researches (Dinnella, Masi, Naes, & Monteleone, 2013; Nguyen, Wahlgren, Almli, & Varela, 2017). For each time interval, only values above the significant level were used and the scores were the average of the scores given to an attribute during an evaluation weighted by their duration (Labbe et al., 2009).

The ANOVA was carried out on the scores, considering sample (fixed effect), replicate (random effect), assessor (random effect) and their interactions as sources of variation (Lea, Næs, & Rødbotten, 1997). In each time interval, only dominant attributes (TDS, M-TDS) or applicable attributes (TCATA) were subjected to the ANOVA model with the purpose of testing the significant differences between respective samples, which had dominant or applicable attributes were detected. The Multiple Factor Analysis (MFA) (Escofier & Pagès, 1994) was applied to the scores. Product spaces and correlation plots were constructed to visualize sample differences and/or similarities in sensory attributes with corresponding time intervals.

The Canonical Variate Analysis (CVA) was conducted based on a multivariate analysis of variance (MANOVA) model with product being a fixed effect, whereas subject as a random one. This is slightly different from standard CVA since it contrasts the between-samples covariance matrix with the interaction covariance matrix (interaction between assessor and samples) instead of the within-group covariance matrix. By doing so, CVA draws the product map based on product means with consideration of subject variability (Peltier, Visalli, & Schlich, 2015b).

To quantify the degree of collinearity in the data, the distribution of Singular Value Decomposition (SVD) was assessed as proposed by Callaghan and colleagues (Callaghan & Chen, 2008). The CVA biplots allowed differences between samples to be visualized while taking account of panelist heterogeneity. Considering k dimensions of sample space, the Hotelling's T-square test was employed to test the hypothesis H0 (the 2 product mean vectors have the same location in the space generated by the first k dimensions). The significant p-value indicated that the mean vectors were statistically different; NDMISIG was the number of dimensions in which the differences between products were significant. Confidence ellipses (90%) have been drawn around each product (Albert, Salvador, Schlich, & Fiszman, 2012; Monrozier & Danzart, 2001; Peltier, Visalli, & Schlich, 2015a; Teillet, Schlich, Urbano, Cordelle, & Guichard, 2010).

The two criteria, namely discrimination ability and agreement, were proposed to assess the panel performance (Lepage et al., 2014; Pineau & Schilch, 2015).

All data were collected with EyeQuestion (Logic8 BV, The Netherlands) and carried out using R version 3.4.1 (R Core Team,

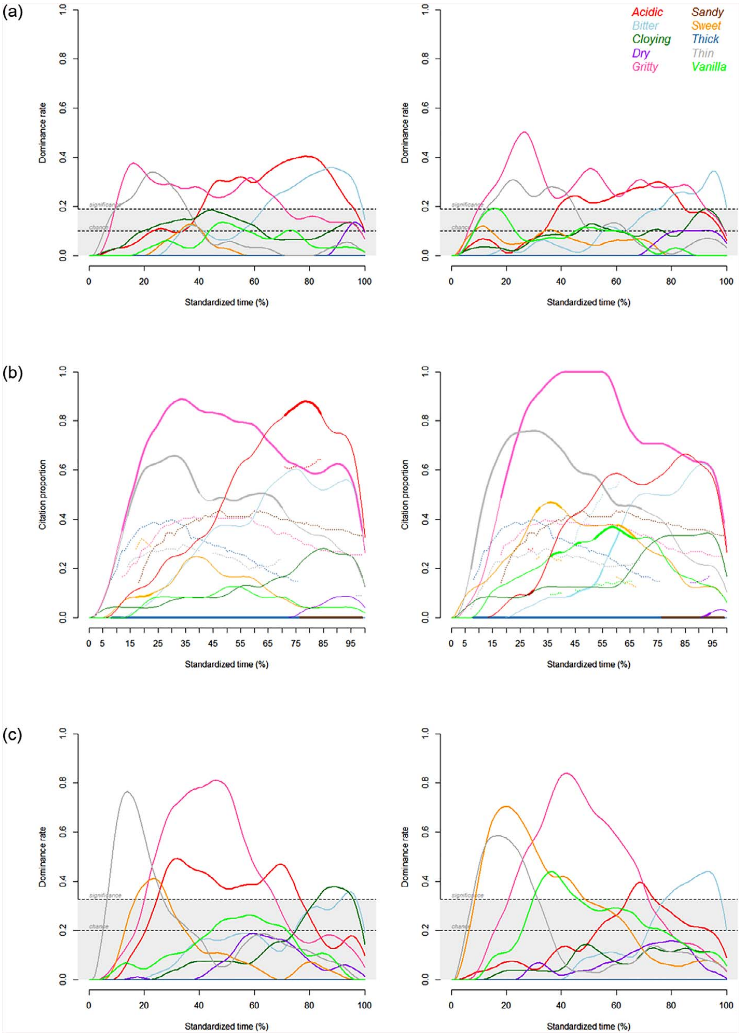

Fig. 1. Temporal curves by sample P1 (left) and sample P5 (right) evaluated by TDS (a), TCATA (b) and M-TDS (c).

2017).

3. Results

The key point of this research is to focus on the similarities and differences between the temporal methods. Another discussion point will be what research questions can answer each of the methods. For brevity, the details of the specific sensory profiles of each of the samples were not presented here, but they are available on supplementary material to the interested reader. The next three sections will give topline results for the three methods, and Fig. 1 shows exemplar TDS, TCATA and M-TDS curves for two samples P1 and P5 only varying in flavour intensity.

3.1. Dynamic sensory profiling

3.1.1. TDS

The TDS curves showed that texture attributes were the first dominant perceptions for all samples, regardless of the viscosity, particle size or flavour level. For flake-added samples, *Gritty* was dominant at the beginning of the oral processing, coupled with *Thick* or *Thin* depending on the viscosity of the samples. Similarly, *Sandy* was the dominating texture for flour-added samples at the beginning following *Thin* or *Thick*. Those dominances lasted for 30–40% of the eating time. The dominance rates were higher than the significance level, but their values were generally low to medium, (0.4–0.6), showing that, in general, the attributes did not obtain very high consensus in the TDS evaluation. In the middle of the eating process, *Acidic* was dominant for all samples, and *Bitter* in the middle and end. These perceptions were associated to particle size and flavour intensity. The flour induced a decrease in the dominance of *Acidic* and enhanced *Bitter* dominance regardless of the flavour intensity. In general, samples were less dominantly *Acidic* in optimal level samples. In the last stage of the oral processing, *Bitter* dominant in all samples. It is interesting to note that although *Sweet* and *Vanilla* were selected as important by the panelists to differentiate the samples at attribute selection stage, they were not

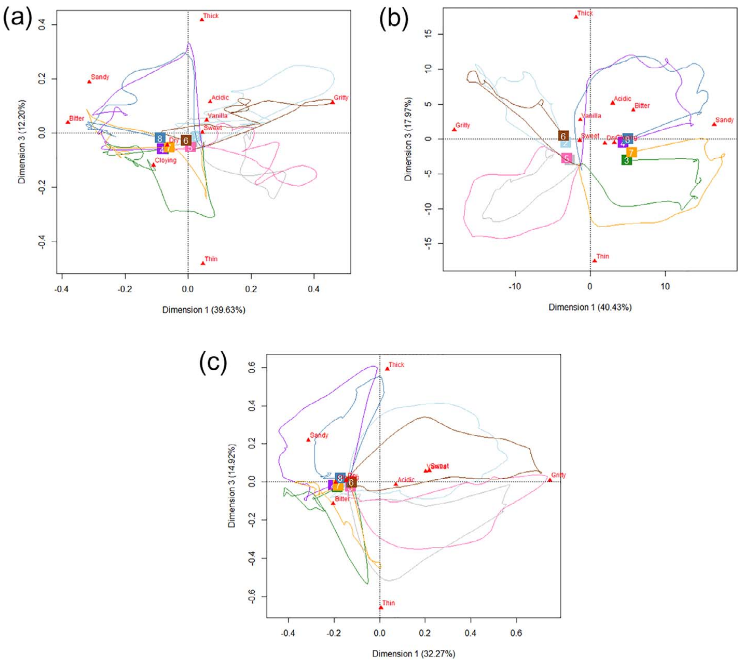

Fig. 2. Smoothed trajectories resulting from PCA on dimensions 1, 3. The sample labels were positioned at the end of the trajectories.

found as dominant at any moment of the consumption in the TDS test.

3.1.2. TCATA

The temporal profiles of low flavour samples were mainly characterized by texture attributes during all eating process. *Gritty* and *Sandy* were applicable throughout all consumption period. *Dry* was applicable in the second half of the eating period significantly higher than the average for the thin flour samples. This might suggest that the perception of *Dry* was enhanced when viscosity was low, while the thicker texture acted as a lubricant in the tongue against astringent flour particles. The increase in flavour in the optimal level caused an increase in sweet-related sensations considered applicable (*Sweet*, *Vanilla*); in particular, *Sweet* in the beginning and *Vanilla* in the middle of the eating process.

While TCATA highlighted *Sweet* and *Vanilla* flavours as significantly more applicable than the average in the optimal samples, and in some of the low flavour samples, in TDS these two flavours were below the significant line for most samples.

3.1.3. M-TDS

The M-TDS curves indicated that the initial dominant perception was related to the viscosity properties (*Thick*/*Thin*). The attributes linked to particle size, *Sandy* for the flake samples and *Gritty* for the flour samples, began to be perceived as dominant at 20% of consumption time for all samples, and lasted up to the beginning of the final consumption stage. *Sweet* was selected as dominant attribute for all samples in the beginning of the consumption. Its dominance rate ranged from 0.35 (low flavour samples) to 0.7 (optimal flavour samples) at about 40% of the beginning of the consumption period, meaning than M-TDS highlighted the flavour differences between the samples more than TDS. Importantly, for optimal flavour samples, *Vanilla* was also detected as significantly dominant in this time slot. This was the other apparent difference between TDS and M-TDS curves, as TDS did not highlight *Vanilla* as dominant in any of the samples. At the end of the eating process *Bitter* and/or *Cloying* perception was dominating for all the samples except for sample P8.

More specifically, Fig. 1 shows exemplar TDS, TCATA and M-TDS curves for two samples P1 and P5 only varied in flavour intensity. TCATA curves displayed the proportion of citations for each attribute at each time of the evaluation in which thicker curves show attributes that are more (less) cited than the average at a particular point in time of consumption. For sample P1, the three methods presented similar sensory patterns; the assessors perceived *Thin* and *Gritty* in the first half and then *Acidic* in the second half of the eating process. For the same pattern, M-TDS seems to have discriminated slightly better the sequence *Thin-Gritty*. Nonetheless, the differences among the sensory descriptions between methods appeared when the flavour intensity was increased in the sample (P5). In TDS, perceptions linked to sweet perceptions (*Vanilla, Sweet*) were not dominant, whereas, for TCATA and M-TDS, they perceived *Vanilla* at the beginning and *Sweet* at the middle of the mastication as more applicable or dominant respectively. Note that the assessors even selected *Sweet* as more applicable or dominant at the beginning when they evaluated the low flavour intensity sample (P1). This implies that TCATA and M-TDS seem to be more efficient when unveiling the dynamic flavour characteristics of the samples.

In addition, differences between citation proportions in TCATA and dominance rates in TDS/M-TDS were observed in all attributes. On average, citation proportions in TCATA were larger than those in TDS, in most cases above 0.8 in TCATA and around 0.4–0.5 for TDS. The forced choice in TDS might explain the lower citation proportion as compared to TCATA. In principle, all the attributes in the list could be cited all along the evaluation in TCATA, but this is not the case for TDS where the probability of citation is always 1/number of attributes. One possible explanation is due to the lack of consensus among assessors on which attributes were dominant. The lower consensus can be due to several concurrent dominant attributes, added to the complexity to the concept of dominance. Consequently, several attributes did not reach significance throughout the evaluation. This complexity could in principle be a valuable result in itself although a difficult one to get direction from.

Regarding method difficulty, in this study, none of the assessors commented about a major complexity or difficulty in the TCATA task. This is in agreement with previous studies on self-reported task perception measures (Ares et al., 2016, 2015). In fact, this particular panel feels more comfortable evaluating temporal perception by TCATA rather than TDS, expressing themselves more freely with TCATA, while in TDS they feel somehow restricted, also explored in Varela et al. (2017).

3.2. Product trajectory

The PCA scores from adjacent time points were joined to give the trajectories, which were presented in Fig. 2. Trajectory plots display the path that follows the sample throughout the sensory space while the sample is consumed (Lenfant et al., 2009), summarizing the evolution of dynamic profile over time. Dimension two accounted for the second largest variability in data, linked to proportions dimension of all attributes, not adding relevant information about the profiles. Thus, dimensions one and three were chosen as the best for displaying differences between samples in the three cases.

The first dimension of the PCA for the three methods was correlated to the attributes *Gritty* on the one side and *Sandy* on the opposite side, separating the samples according to the particle size of the oats. In particular, samples P4, P8, P7, and P3, formulated with oat flour were grouped on one group, whereas the rest (with oat flakes) belonged to the other group.

Meanwhile, the third dimension of the PCA in the three methods was mainly associated with the viscosity attributes (*Thick*/*Thin*). Samples P2, P6, P4 and P8 were characterized by the *Thick* attribute while samples P1, P5, P3 and P7 by *Thin* attribute.

As mentioned previously, the PCA plots also pointed out evolution of samples over time. The trajectories visualized the common pattern in temporal profile. The products could be split into two groups according to their sensory trajectories: one group with high viscosity (P2, P6, P4 and P8), another group with low viscosity (P1, P5, P3 and P7). The former group was characterized as being *Thick* at the beginning of the eating process, then *Gritty* (samples P2, P6) and *Sandy* (samples P4, P8). The latter group was described by *Thin* at first, turning into *Gritty* and/or *Sandy* at the end of the eating process. In general, flavour attributes did not strongly influence the sample trajectories except for TDS trajectory; *Bitter* was pointed as dominant attribute in the last stage of the eating process for the flour samples (P3, P7, P4 and P8). The attribute partly imparted on temporal sequence of sensations during consumption of samples P4 and P8 in TCATA trajectory.

In general, the evolution pattern was similar among methods. The TDS trajectories, however, was the less resolved. One explanation was possible due to the dithering in selecting a dominant attribute of the panelists, which in turn made the low consensus in their results.

3.3. Product characterization

Regarding QDA results, the 2-way ANOVA indicated that the panelists well discriminated between the samples for all the sensory attributes, except for *Acidic taste* and *Sickening odour*. Two other performance indexes, agreement and repeatability abilities, were also assessed. Nevertheless, the indexes were not the main focus in this study, so they have not been deeply discussed.

To evaluate the sensory profiles provided by each method and to compare them together, a MFA was performed on the combined data composed of TDS, TCATA, QDA, TDS by modalities (flavour, texture) sensory profiles. Each profile was considered as a separate data table in MFA. Within each group, only significant attributes in the three time intervals were selected in the calculations. The MFA analyses were started by examining the canonical correlation coefficients. These coefficients measured the relationship between MFA dimensions and each group of data. Table 4 shows the values of these coefficients, in particular, to TDS, TCATA and QDA groups clearly explained by Dim1, whereas M-TDS by Dim2. The next criterion to evaluate was the RV coefficient (Table 5). As compared with QDA, the RV coefficients of TDS, TCATA and M-TDS were 0.69, 0.83 and 0.39, respectively. This implied a strong link existed between the TCATA and QDA profiles. Graphically, the relationship between the groups and the common space provided by the MFA was evaluated through the partial axes representation (Fig. 3). Without concerning the sign of the correlation, Fig. 3 shows the relationship between MFA dimensions and dimensions of each group (TDS, TCATA and M-TDS). It is worth noting that, the third dimension, instead of the second dimension of M-TDS, linked to the first MFA plane.

The superimposed representation (Fig. 4a) was other important result, indicating how close the different points of view could be, within each product. It suggested that, for any sample, the way how the samples characterized by each method was distinctive. Of those, QDA, TDS and TCATA methods offered similar descriptions, reflecting by the same direction of these methods on the map. Conversely, the standpoint provided by M-TDS was very extreme compared with three methods QDA, TDS and TCATA. It was not surprising as M-TDS was carried out by two sequential modalities, which might be failing to assess the interactions between modalities. Furthermore, the correlation between TCATA and QDA on the map was high, implying that the TCATA description was more highly correlated to the QDA description than to the

Table 4
Canonical correlation coefficients from MFA.

Group	Dim1	Dim2	Dim3
TDS	0.97	0.90	0.75
TCATA	0.98	0.96	0.78
QDA	0.94	0.85	0.61
M-TDS	0.82	0.97	0.94

Table 5
RV coefficients from MFA.

	TDS	TCATA	QDA	M-TDS
TDS	–	–	–	–
TCATA	0.79	–	–	–
QDA	0.69	0.83	–	–
M-TDS	0.53	0.55	0.39	–

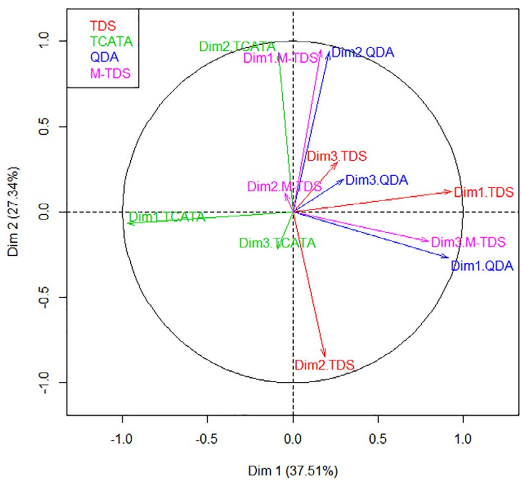

Fig. 3. Partial axes plot resulting from the MFA performed in combined data composed of QDA, TCATA, TDS and TDS by modalities.

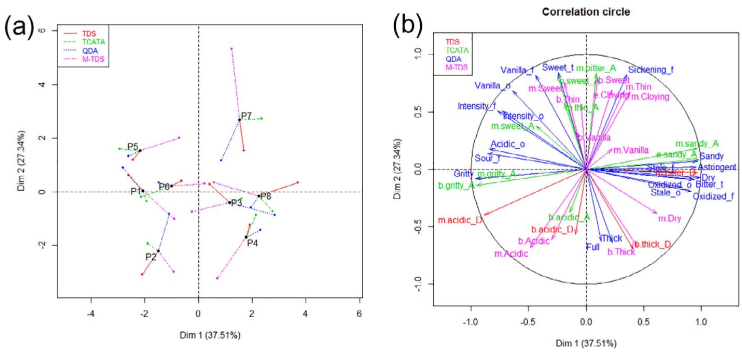

Fig. 4. The superimposed representation and perceptual map from the MFA performed in combined data composed of QDA, TCATA, TDS and TDS by modalities. b: beginning; m: middle, e: end of the eating process.

TDS description.

The perceptual map (Fig. 4b) displays the links between attributes of each method. The results indicated that the same perceptions provided by different methods were highly associated, except for Acidic and Bitter. It is noteworthy that Bitter perception evaluated by TDS and TCATA was not correlated. The *m.Bitter* provided by TDS was mostly explained by the first dimension, the *m.Bitter* provided by TCATA, conversely, taken into account by the second dimension. On the first space (Dim1 vs. Dim2), two perceptions were orthogonal. Regarding Acidic perception, it was perceived differently between TDS and the rest of methods; *m.Acidic* by TDS was not highly correlated to Acidic perceptions of TCATA and M-TDS methods.

To better understand these differences, ANOVA was carried out (Table 6). For each attribute, only the samples dominated and/or applied were compared. All methods showed similar results. The difference was observed between two groups of samples; one group consisting of the samples P1 to P4, another group comprising the samples P5 to P8. The former was formulated with low sweetener intensity while the latter with optimal sweetener intensity. The increase in sweetener intensity resulted in the decrease in perceptions of both *Acidic* and *Bitter*.

3.4. Panel performance

The significant attributes were identified by the ANOVA (Table 7), in which the rows corresponded to the sensory attributes of the data set, the columns to the temporal methods, and each element corresponded to the *p-value* associated with the *F-test* of an effect for a given attribute.

The MANOVA results addressed the multidimensional discrimination, a measure of the separation of the samples in the sensory space generated by the descriptors relatively to panelist disagreement.

The multicollinearities were checked for each of the datasets. As

Table 6
p-Values from Tukey's HSD test for the two attributes *Acidic*, *Bitter*.

	b.Acidic			m.Acidic		m.Bittter	
	TDS	TCATA	M-TDS	TDS	M-M-TDS	TDS	TCATA
P1	0.07^{ab}	–	0.23^{a}	0.33^{a}	0.40^{ab}	0.17^{b}	–
P2	0.19^{a}	0.22^{ab}	0.23^{a}	0.35^{a}	0.46^{a}	0.19^{ab}	–
P3	0.12^{ab}	0.27^{a}	0.25^{a}	0.20^{ab}	0.28^{abcd}	0.33^{ab}	–
P4	0.10^{ab}	–	0.24^{a}	0.17^{ab}	0.31^{abc}	0.32^{ab}	–
P5	0.64^{b}	0.09^{b}	0.05^{b}	0.26^{ab}	0.25^{abcd}	0.11^{b}	0.31^{b}
P6	0.07^{b}	–	0.03^{b}	0.23^{ab}	0.20^{bcd}	0.21^{ab}	–
P7	0.09^{ab}	–	0.02^{b}	0.10^{b}	0.07^{d}	0.34^{ab}	0.62^{a}
P8	0.53^{b}	–	0.05^{b}	0.09^{b}	0.10^{cd}	0.42^{a}	–

Different letters in the same column indicate statistical differences ($p < .05$) among the products.
b., m. was the notation of beginning, middle time intervals.

Table 7
Significant attributes resulting from ANOVA (p-value).

	TDS	TCATA	M-TDS
b.Acidic	0.093	0.100	< 0.001
b.Gritty	–	< 0.001	–
b.Sweet	–	0.006	0.007
b.Thick	0.051	–	< 0.001
b.Thin	–	–	< 0.001
b.Vanilla	–	–	0.022
m.Acidic	0.029	–	0.020
m.Bitter	–	0.074	–
m.Cloying	–	–	0.023
m.Dry	–	–	0.001
m.Gritty	–	< 0.001	–
m.Sandy	–	< 0.001	–
m.Sweet	–	0.086	0.013
m.Thin	–	0.086	0.007
m.Vanilla	–	–	0.011
e.Bitter	0.021	–	–
e.Cloying	–	–	0.007
e.Sandy	–	< 0.001	–

b., m. and *e.* were the notation of beginning, middle and end time intervals.

shown in Fig. 5, the values of SVDs did not decrease dramatically, indicating the weak degree of collinearity of datasets. In addition, the sample configurations obtained by CVA also were compared with those of PCA. The comparison indicated that the maps were not too different between CVA and PCA approaches (results not shown). These results were displayed in Fig. 6. The Hotelling's T-square test discriminated all pairs of samples. In TDS biplot (Fig. 6a), two samples P1, P5; three samples P6, P3, P7; and two samples P4, P8 were connected with the other segments, respectively. In TDS map, these segments were located closely to each other as compared with TCATA map (Fig. 6b) and M-TDS map (Fig. 6c). This implied that the sample discrimination in TDS was less effective than in TCATA and M-TDS.

The distribution of panelist scores around the product means could be visualized by confidence ellipses, showing the (dis)agreement between panelists. In TDS, the consensus in selecting dominant attributes was low, resulting in the high variability of the subject scores around the mean. In Fig. 6, the sizes of confidence ellipses in TDS was the largest, whereas those in TCATA and M-TDS were smaller. It is thus possible to confirm the better agreement ability of panelists in TCATA and M-TDS tasks.

4. Discussion

4.1. Comparisons based on product description

Apart from citation proportions and dominance rates, the difference among temporal methods is apparent when comparing the temporal

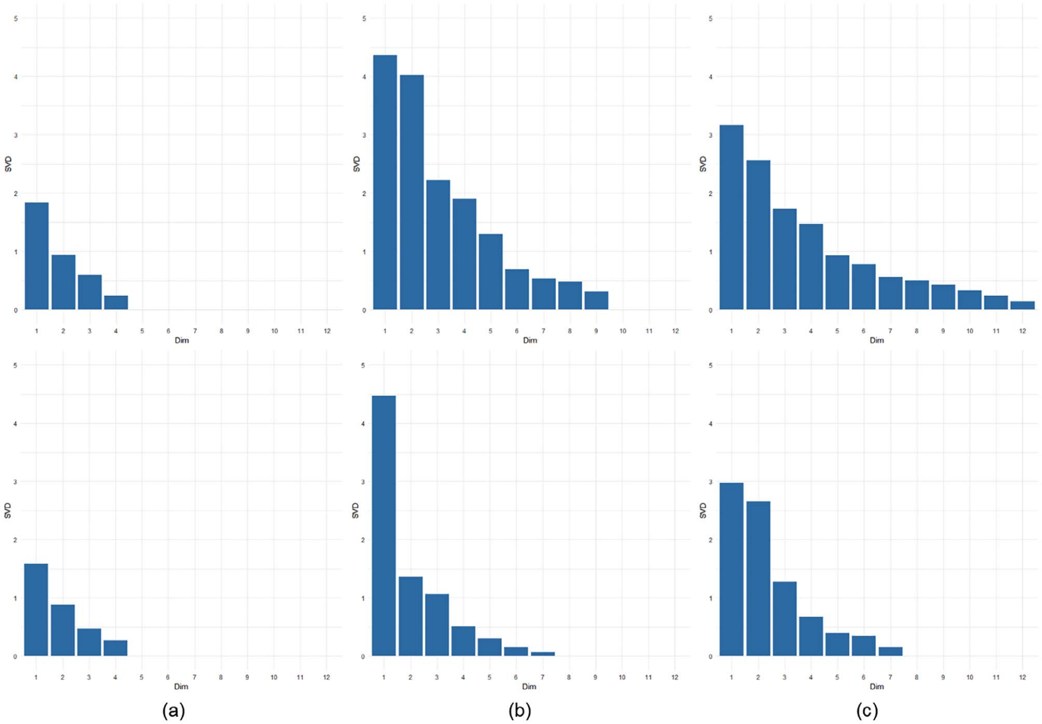

Fig. 5. The distributions of SVD for sample covariance matrix (*top*) and interaction covariance matrix (*bottom*) in TDS (a), TCATA (b) and M-TDS (c).

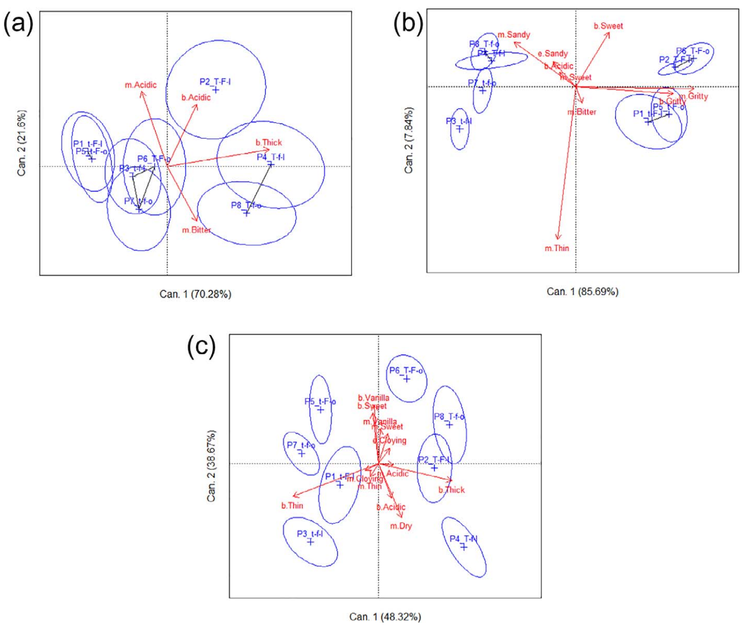

Fig. 6. The CVA biplots for TDS, TCATA and M-TDS methods.

profiles of the optimal flavour samples. The key point is the information related to sweetness; the assessors did not select *Sweet* and *Vanilla* as dominant when tasting samples at any point in the TDS task. The reason can be attributed to the nature of perception. Texture and taste perceptions are more dominant and easier to use and to choose as dominant by panelists to describe products than aroma perception, emphasizing the fact that these attributes are the most discriminating (Kora, Latrille, Souchon, & Martin, 2003; Saint-Eve et al., 2011; Wendin, Solheim, Allmere, & Johansson, 1997). Besides, aroma attributes are perhaps less frequently used than others when a choice has been made from among all of the attributes (Saint-Eve et al., 2011). The panelists, tended to choose mainly textural attributes as dominant when they could choose only one in this example. It is possible to overtake the problem by using alternative procedures such as TCATA or M-TDS. Here, the panelists could select many applicable attributes at a time in the TCATA task, or both texture/flavour as dominant at the same time, because of having them in separate screens in the M-TDS task. As a result, *Sweet* and *Vanilla* appeared as applicable and/or dominant at the beginning and middle of the eating process, respectively.

For TDS tasks, the selection of dominant attributes followed the texture – flavour process. It is somehow logical because the dominant processes are described in hypothetical food-saliva systems, in these sequential steps: comminution – agglomeration – hydration – dilution (Witt & Stokes, 2015). The TDS results showed that texture attributes, were always perceived as dominant at the beginning, and *Bitter* taste dominated at the middle and end of the eating process. Here, it is not certain that sweet related attributes were not selected because they were not dominant (as compared to the rest of the taste/flavour attributes) or if the panelists would always select texture, driven by the natural oral processing sequence. Furthermore, with continuing size of fractured particles reduction, texture perception will become less relevant, and hugely increased surface area helps fast release and diffusion of taste and aroma compounds from food interior. Both phenomena could cause that *Bitter* can be detected as the dominant attribute at the second half of the eating process. In this context, it is also interesting to note, that bitter is an alerting sensation -with the evolutionary object of pinpointing dangers, as poisons- then it could be that cognitively, humans are prepared to detect bitter more dominantly over other tastes or flavours.

Results confirm what Varela et al. (2017) suggested, that in TDS tasks, different modalities are in competition for the "dominance" rating. One could think of some products where texture might be definitely dominant as compared to flavour, highly crispy products for instance, or also some foods where flavour might be much more dominant than texture, espresso coffee for example. Nevertheless, most products would have one flavour and one texture attribute *dominating at the same time*. Flavour and texture are really perceived by different channels, chemesthesis (chemically induced sensations in the oral and nasal cavities) vs somesthesis (tactile and thermal sensations) (Lawless & Heymann, 2010b). So, how is it possible to compare sensations perceived by those two channels and being able to choose only one attribute of one of the modalities? This is a complex decision a panelist needs to do, and that is reflected by the low agreement in TDS tasks, and the high level of noise in the data, due to dithering and dumping effects determined by the difficulty in deciding on the dominant attribute and shifting to the next (Varela et al., 2017).

Food perception is a multisensory phenomenon, reflecting the integration of taste, olfactory, and other sensory information into a perceived property of the food, rather than a collection of individual sensory attributes (Prescott, 2015). In addition, the normal or free oral processing is the most efficient way to judge the sensory attributes of semi-solid foods (de Wijk, Engelen, & Prinz, 2003). These suggest that sensory perceptions should be evaluated simultaneously in order to avoid loss of relevant information. In this context, TCATA seem to reflect better the multisensory experience in food consumption and its relation to the natural oral processing and dynamic sensory perception. Of course, if the objective of the research was to highlight a single dominating sensation, even in the case competing modalities or perceptual channels, TDS will be the method of choice. However, one should be aware that most of the times that would mean that TDS will highlight textural aspects when food physics dominate the consumption phase (beginning and sometimes end of the mastication), irrespectively of how one would change the flavour of the product.

The sample trajectories show the different way how sample characteristics change over time. This observation corroborates that texture properties have a large influence on sensory perceptions of samples. In this study, the viscosity-related attributes were selected at the early stage of eating period, together with particle size attributes. Importantly, *Gritty* and *Sandy* were the most important attributes in the first dimension of PCA biplots, but they are not the first attributes that panelists use to separate samples. In practice, they used *Thick/Thin* as the first classifier. The results support the idea that there seemed to be a privileged time window of expression of some specific sensations in the course of the eating period (Lenfant et al., 2009). According to Allen Foegeding, Çakır, and Koç (2010), the sequence of sensation can be grouped based on the different stages of the in-mouth processing of food: pre-fracture, first bite, chew down and residual after swallowing. Some authors (Chen & Stokes, 2012; de Wijk, Janssen, & Prinz, 2011) found that sensations of those bulk-dominated texture features were detected relatively quickly, whereas sensations of those related to surface properties were detected relatively slowly. That is the important transition of oral sensation of textural properties from rheology to the tribology domain. Consequently, in this case, the attributes related to viscosity (*Thick/Thin*) are perceived first, and then the attributes concerning particle size (*Gritty/Sandy*) were dominating or significantly more applicable later in the consumption. These brings back to the topic that modality or groups of attributes, rather than single attributes could be what drives the dominating sensations throughout the eating process, encompassing the natural oral processing mechanisms, process which TCATA would allow to reflect.

4.2. Comparisons based on panel performance

As testing panel performance, the results were in light with previous research (Ares et al., 2015) that showed TCATA provided a more comprehensive overview of temporal sensations than TDS did. The present study also showed that a modification of TDS (M-TDS) allowing for different modalities to be chosen at the same time, could overcome the above discussed issues that make TDS less efficient. Evidence of better discrimination of TCATA and M-TDS supports the idea that only one dominant attribute chosen at a given time leads to missing relevant information of the sensory characteristics of food products. In addition, panelists show a good agreement for describing the samples. This indicates that TCATA is not a complex and fatiguing method for panelists and can be used to obtain a reliable description of the dynamics of sensory perception.

4.3. Which method for which research question

The methods compared in this work are based on different conceptual aspects (applicability vs dominance), and there is still a lot of research and thinking to do, particularly in terms of which methods answer to which research questions. The results of the present study suggest that TCATA task could be recommended to capture in a more natural way the dynamic and multisensory perceptions of food products, where assessors could freely choose the number of sensations relevant at each moment. M-TDS on the other hand, also seems to retrieve the multisensory aspects of the dynamics of perception, and could be recommended when one is interested in dominance, or how one sensation could overshadow others in a product at different points in time, without losing sight of product complexity. TDS however, generates a more restricted outcome, less discrimination between products, and the biases because of attribute restriction could be limiting at the time of interpreting results (see Varela et al. (2017) for an in depth discussion of the dumping and dithering effects in TDS evaluation). Some researchers suggest the TDS could be better suited to consumers than to trained panelists (Schlich, 2017; Varela et al., 2017), however, the majority of the research done so far in TDS has been with trained panels (Schlich, 2017); so more research is definitely needed to see what aspects of consumer perception TDS can reflect. In this sense, it will be interesting to better understand how much are temporal dominant attributes in a product relevant for preferences, food reward, food intake, etc. Some authors (Thomas, Visalli, Cordelle, & Schlich, 2015) suggested TDL (temporal drivers of liking) as a tool for looking into temporal liking; other authors (Delarue & Blumenthal, 2015) have presented some research also in their review on temporal aspects of consumer preferences, but not much research has been done in this area. The main question would be, how is temporality of sensory perception linked to product appreciation and intake? And which is it the best method for looking into it?

Another point worth discussing is the difference in evaluation processes, from perceptual and cognitive points of view; in principle, applicability as measured by TCATA, seems to be quite different than evaluating dominance, as in TDS or M-TDS, i.e. "tick all what is there" as compared to select "the one" dominant attribute. However, the present results suggest that M-TDS is somehow closer to TCATA than to TDS, even if it relies in dominance evaluation. Then, one could think that applicability and a less restricted dominance are not that far in approach. Particularly thinking that the applicable attributes in TCATA need to be chosen in a very fast sequence, one could think that the "most applicable attributes" would in a way be also the "most striking", generating a less restrictive selection of a higher number of "dominant" attributes. This point would definitely be worth further studying in future research.

5. Conclusions

This paper presents a reasonable and meaningful basis for monitoring and comparing performances of three temporal methods (TDS, TCATA and M-TDS). The multiple selection of attributes (totally in TCATA or partly in M-TDS) at a given time provides a better dynamic sensory characterization. TDS provides a meaningful description of the attributes if for some reason one is interested in one attribute only to be selected at a time. M-TDS however, still looks into dominance as a concept, but allows for different modalities to be represented, obtaining a richer description, but also more robust results than TDS. TCATA would bring even additional information where interaction between attributes is required and allows to represent more than two attributes at any point in time.

In the current research, TDS was performed according to the definition of dominance attribute proposed by Pineau et al. (2009). However, a general consensus has not been reached among researchers regarding the concept of dominance and thereby it should be further discussed in future studies. One limitation of this study is the fixed order in which methods were carried out, that is, TDS, TCATA and then M-TDS, next studies could include a randomised allocation to method to the different panelists.

Future research should go deeper in methodological comparisons of TDS, M-TDS and TCATA, to better understand what specific questions could be answered by the different methods, and what are their advantages and limitations for specific product categories. This could include comparison between different panels with the same training, as well as using consumers instead of trained panelists systematically to being able to further conclude on recommendations for application.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodqual.2018.01.002.

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PAPER 3

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Portion size selection as related to product and consumer characteristics studied by PLS path modelling

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ABSTRACT

Expectations of satiation and satiety have been increasingly investigated because of the interest in how they, along with liking, can modulate portion-size selection. Consumer characteristics can also be important when consumers select their portion size. However, the contribution and interaction of consumers and product aspects to portion size selection has not been unveiled. This study aims to better understanding these complex relations by simultaneously assessing the relative influence of consumer characteristics and product related properties on portion size selection utilizing PLS-Path Modelling (PLS-PM) approach.

In this study, consumers (n = 101) answered questions regarding attitudes to health and hedonic characteristics of foods, and completed hunger and fullness questions. In an evaluation step, they tasted eight samples of yogurt with different textures and rated liking, expected satiation, expected satiety and portion size. The consumers were also classified on their mouth behaviour by using the JBMB™ tool.

Results showed that *liking*, *satiation*, *satiety* and *portion size* depended firstly on the thickness, and then on the particle size of samples. PLS-PM was used to generate a model, indicating that *liking* was a direct predictor of *portion size*, with a stronger effect than *satiation* or *satiety*. The relationship between *liking* and *satiety* was observed both in direct direction (*liking-satiety*) and also indirect direction throughout *satiation* (*liking-satiation-satiety*). The former was negative effect and the latter was positive effect depending on the criteria which consumers used.

These findings implied that *liking* is a main factor in the prediction of *portion size* however the relations are complex.

1. Introduction

1.1. Satiation, satiety and consumers' expectations

Until now, many studies of meal size have indicated that when deciding on a particular portion size, our strategy may be guided by a concern to ensure that a portion of food will deliver adequate satiety (Brunstrom & Shakeshaft, 2009). Satiety comprises two processes: satiation (intra-meal satiety) and satiety (post-ingestive satiety or inter-meal satiety). The former is defined as the process that leads to the termination of eating; therefore, controls meal size. The latter is the process that leads to inhibition of further eating, decline in hunger, increase in fullness after a meal is finished (Blundell et al., 2010).

Satiation is measured through the measurement of *ad libitum* food consumption of particular experimental foods (weight in grams or energy in kcal or kJ) under standardized conditions. Satiety is usually measured using a preload-test meal paradigm (Blundell et al., 2010). Expectations of satiation and satiety without consuming a whole portion, but relying on a prospective portion size (de Graaf, Stafleu, Staal, & Wijne, 1992; Fiszman & Tarrega, 2017), have been used to measure satiation and satiety in many studies.

Brunstrom and colleagues have showed that people have very precise expectations about satiety and satiation that foods are likely to confer (Brunstrom & Rogers, 2009; Brunstrom & Shakeshaft, 2009; Brunstrom, Shakeshaft, & Scott-Samuel, 2008). In general, expected satiety can be quantified by asking the participant to select the amount that would be needed to stave off their hunger for a specific period of time, whereas expected satiation can be quantified by selecting the amount that would be required to feel full. Ideal portion-size can be assessed by asking the participant to select the amount that they would

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typically consume or the amount that they would like to consume at that moment (Wilkinson et al., 2012).

1.2. Satiety-related perceptions and portion size selection

Two foods of equal nutrient content may have different effects on appetite. This is because aspects of food consumption, other than the metabolic effects of nutrients in the gastrointestinal tract, contribute to processes involved in appetite control (Chambers, 2016). The 'Satiety Cascade' (Blundell et al., 2010) describes that both expected satiation and satiety of foods rely on sensory attributes of foods. Among sensory dimensions, texture imparts expectations of satiation and satiety clearer than flavour does (Chambers, 2016; Hogenkamp, Stafleu, Mars, Brunstrom, & de Graaf, 2011). Food texture can influence at several levels. First, texture plays a critical role in satiation or satiety through its effect on oro-sensory exposure. Due to their fluid nature, liquid foods require less oral processing time than semi-solid and solid foods, leading to reduction in oro-sensory exposure, which is important for the development of satiety related perceptions (McCrickerd, Chambers, Brunstrom, & Yeomans, 2012; Tang, Larsen, Ferguson, & James, 2017). More specifically, longer mastication duration and higher intensity of sensory signals are also linked to higher satiation (Blundell et al., 2010; Bolhuis, Lakemond, de Wijk, Luning, & Graaf, 2011). Second, from a cognitive perspective, people may think solid foods are more satiating than liquid foods, i.e. solid foods will contain more energy than liquid foods, without necessarily reflecting their actual calories (de Graaf, 2012).

1.3. Palatability and portion size selection

In addition to the expectations of satiation and satiety, palatability of food is seen as an important determinant of portion size selection. The role of palatability in prediction of portion size, however, has been debated over different studies. Some studies indicated that reducing the palatability of our diet should result in reduced food consumption (Yeomans, Blundell, & Leshem, 2004). Likewise, incremental increases in palatability lead to short-term overconsumption; that is, we consume more of foods that we like (Cooke & Wardle, 2005; Yeomans, 2007). Nevertheless, other studies found that palatability was not associated with the selection of portions and then rejected the hypothesis of these palatable foods tend to be selected in relatively larger portions (Brunstrom & Rogers, 2009). Recently, the question whether "quality can replace quantity" has been raised in some studies. It has been found that palatability is unable by itself to predict people's food behavior. Instead food reward, an immediate sensation of wanting and liking a food when it is eaten and as a longer lasting feeling of well-being after a meal, could be used to predict the behavior. Under the assumption that well-tasting/high sensory quality foods provide more reward per energy unit than bland foods, the hypothesis that 'quality can replace quantity' has been supported (Møller, 2015a, 2015b).

It is important to note that expected satiation, satiety and hedonic quality influence each other and together they influence portion size. Nevertheless, the ways in how these expectations are related are still unclear; while some studies showed that if people eat a food they greatly enjoy, they will experience more pleasure, satiation and satiety (Bobroff & Kissileff, 1986; Mattes & Vickers, 2018; Rogers & Schutz, 1992), others observed that increased liking decreased feelings of satiety or satiation (Hill, Magson, & Blundell, 1984; Holt, Delargy, Lawton, & Blundell, 1999).

1.4. Individual differences in consumer expectations

Individual differences should be considered when evaluating the relations between these expectations. Individuals use different mechanisms for the oral breakdown of food so that at any point, different groups of individuals would experience the samples differently (Brown & Braxton, 2000). The differences might have different impacts on sensory perception, which in turn, would drive consumer expectations (i.e. liking, expected satiation and satiety) (Jeltema, Beckley, & Vahalik, 2015, 2016). Individuals have subjective experiences of satiety which are influenced more by what the person saw and remembered, and less by what they actually ate (Brunstrom, 2014; McCrickerd & Forde, 2016; Wilkinson & Brunstrom, 2009). These experiences should be considered when determining the relations between consumer expectations.

The objective of this paper is to investigate and model from a holistic perspective different aspects of consumer expectations (liking, satiation, satiety) using a PLS path modelling approach. Our study differs from preceding studies in that we consider all consumer expectations simultaneously in the prediction model. In addition, consumer attitudes towards health and taste, experiences relevant for satiety and individual differences were measured. Main attention will, however, here be given to the product related measurements.

2. Materials and methods

2.1. Samples

Eight yoghurt samples were prepared from a design of experiment (DOE) based on the same ingredients, only modifying the product texture by using different processing strategies, so as the samples would have the same calories and composition and these parameters would not influence satiety or satiation. The parameters of the DOE were: viscosity (thin/thick), particle size (flake/flour) and flavour intensity (low/optimal); see (Nguyen, Næs, & Varela, 2018) for details. Table 1 shows the samples with different levels of viscosity, particle size and flavour intensity.

2.2. Consumer test

One hundred and one consumers were recruited for the test in the southeast area of Oslo from Nofima's consumer database (73 females and 28 males, aged ranging between 18 and 77). Participants were regular yoghurt consumers (at least once a week). A recruitment questionnaire was used to collect general information (age, gender, BMI, consumption and usage) and to select consumers based on consumption frequency. Additionally, consumer attitudes were collected through the health and taste questionnaire proposed by Roininen, Lahteenmaki, and Tuorila (1999).

The formal assessment was performed in individual booths and had two parts. The first part was about consumers characteristics: they answered items about hunger and fullness question (Karalus & Vickers, 2016), and attitudes toward healthfulness of food and toward taste (Roininen et al., 1999). The second part was about product characteristics, consumers were asked to taste each sample and rate liking, expected satiation, expected satiety, ideal portion-size, and to describe the samples using Check All That Apply (CATA) questions (Adams, Williams, Lancaster, & Foley, 2007). During the CATA task, they were presented with the predefined list of attributes and asked to indicate which words or phrases appropriately describe their experience with

Table 1
Formulation of the yoghurt samples.

Sample	Viscosity	Particle size	Flavour intensity
P1 (t-F-l)	Thin	Flakes	Low
P2 (T-F-l)	Thick	Flakes	Low
P3 (t-f-l)	Thin	Flour	Low
P4 (T-f-l)	Thick	Flour	Low
P5 (t-F-o)	Thin	Flakes	Optimal
P6 (T-F-o)	Thick	Flakes	Optimal
P7 (t-f-o)	Thin	Flour	Optimal
P8 (T-f-o)	Thick	Flour	Optimal

the product being evaluated. The CATA question consisted of 22 sensory attributes (*Vanilla*, *Sour*, *Oat flavour*, *Sweet*, *Cloying*, *Bitter*; *Fresh*, *Unfresh*, *Thick*, *Gritty*, *Sandy*, *Dry*, *Creamy*, *Mouth coating*, *Chewy*, *Sticky*, *Dense*, *Smooth*, *Heterogeneous*, *Homogeneous*, *Liquid*, *Pieces*) and 13 usage and attitude terms (*Easy to swallow*, *Difficult to swallow*, *High calorie*, *Low calorie*, *Satiating*, *Not satiating*, *Appealing*, *Not appealing*, *Suitable for breakfast*, *Suitable for snack*, *Suitable for supper*, *Fibrous*, *Healthy*). The order of terms was randomized within the two groups (sensory and usage), between products, and across assessors.

Regarding the scales used for the consumer test, the consumers rated liking on a Labelled Affective Magnitude (LAM) scale (Schutz & Cardello, 2001), expected satiation on a Satiety Labeled Intensity Magnitude (SLIM) scale (Cardello, Schutz, Lesher, & Merrill, 2005) and expected satiety on a 6-point scale from 1 = "hungry again at once" to 6 = "full for five hours or longer". For ideal portion-size, they chose the extent to which they would consume as compared to the normal amount of commercial yoghurt product. The portion-size scale, therefore, was one-third to 3-times compared to normal amount. These variables from the first part will be called "consumer related variables" throughout the paper, and those from second part as "product related variables".

Consumers were classified based on their mouth behaviour (MB) using the JBMB™ typing tool, which sorts people in four groups (*Cruncher*, *Chewer*, *Sucker* and *Smoosher*). The tool had consumers classify themselves, by picking the group of pictures and that was "most like them". The descriptions, for example, "I like foods that I can crunch" were followed by foods with textures that were easy to "crunch". It is similar to three remaining groups of *Chewer*, *Sucker* and *Smoosher*. The classification on mouth actions of consumers is based on the fact that individuals have a preferred way to manipulate food in their mouths: some consumers (*Crunchers* and *Chewers)* like to use their teeth to break down foods; while *Suckers* and *Smooshers*, prefer to manipulate food between the tongue and roof of the mouth. The difference within each of the two groups lies in the hardness of preferred foods (Jeltema et al., 2015, 2016). The classification of consumers in MB groups was used to investigate the effect of different mouth behaviours on consumer expectations and prediction models in the rest of this paper.

All the sensory evaluations were conducted in standardized individual booths according to (ISO 8589:2007). Samples were served in plastic containers coded with 3-digit random numbers and in a sequential monadic manner following a balanced presentation order. Thirty grams of each yoghurt was served to each assessor for all the evaluations.

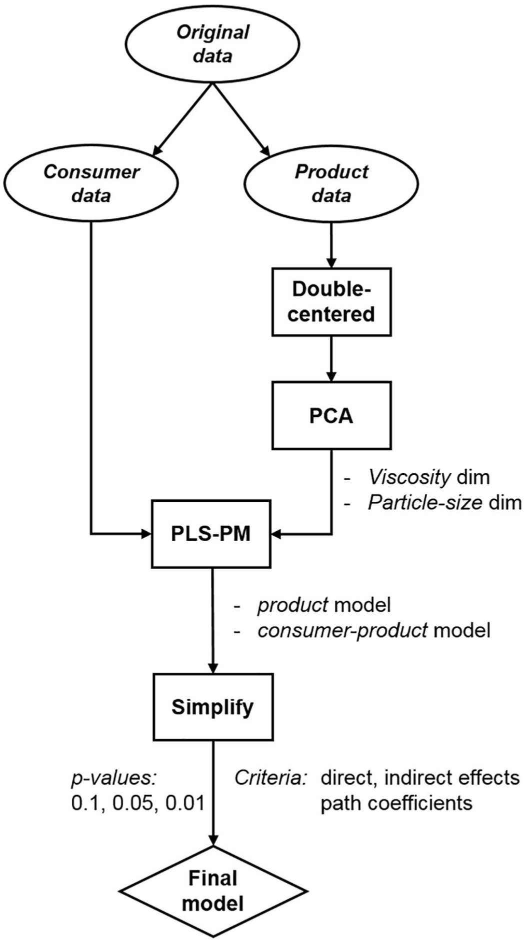

Fig. 1. Schematic diagram of data handling and model selection.

2.3. Data analysis

2.3.1. Analysis of variance (ANOVA) on consumer expectations (liking, satiation, satiety, portion)

Because each consumer would be assigned to only one MB group, consumer and MB group were not crossed. Rather, consumer was nested within MB group. The design was unbalanced as MB groups had different numbers of consumers. The unbalanced nested ANOVA was carried out on the ratings, considering sample (fixed effect), MB group (fixed effect), consumer nested within MB group (random effect) and interactions of sample and MB group (fixed effect) as sources of variation.

2.3.2. PLS path modelling (PLS-PM)

Considering the framework of consumer expectations where liking, satiation and satiety influence each other and together they influence portion size, we will in this paper focus on a path modelling (PM) approach. In particular we chose to use PLS path modelling due to its many good properties (see for instance (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005))

Providing details of the PLS-PM algorithm is beyond the scope of this paper, but they are available from (Tenenhaus et al., 2005; Vinzi, Chin, Henseler, & Wang, 2010).

As indicated in the introduction, main emphasis in the PLS-PM will be given to the product variables, the main reasons being that the consumer variables generally had a weak relation to product related measurements and that the relations were unstable and therefore difficult to interpret when using a model reduction (see below). A brief summary of the results will be given in the results section.

Because these blocks were rated on different scales, standardization between blocks was applied by dividing each block according to the square root of the sum of squares (Frobenius norm).

The procedure for handling data and obtaining model was illustrated in Fig. 1.

2.3.2.1. Organization of data. Since both consumer attitudes and demographics, as measured by a questionnaire, as well as product related aspects such as liking and satiety were measured, a proper organization of the data blocks was needed before submitting the data to analysis. This challenge was discussed in depth by (Menichelli, Hersleth, Almøy, & Næs, 2014). In that paper, it was proposed to let the consumers represent the rows and the different questionnaire questions

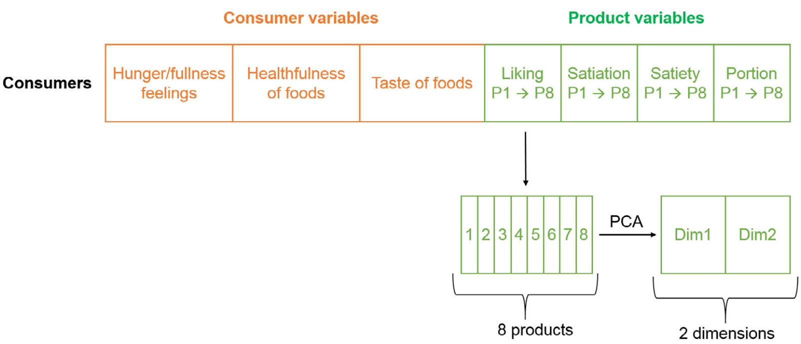

Fig. 2. Different types of data sets and their relations. *The first data set consists of consumer characteristics for each consumer, related to hunger and fullness feelings, attitudes toward healthfulness, taste of foods; The second data set comprises eight ratings (responding to eight products) for each expectation (liking, satiation, satiety, portion) for each consumer. Specifically, there are four data blocks and each of the block includes eight columns with the ratings of the eight products.*

and liking of the different products represent the columns, i.e. each product has a separate column of liking values. In cases with very many products it was proposed to represent the liking values for all products by a few principal components only. We will here use this strategy for all product related blocks, i.e. liking, satiation, satiety and portion. Fig. 2 displays how the data set was organized for analyses.

2.3.2.2. Solving the one-dimensionality issue. It is generally most appropriate to model sensory variables and also possibly habits/attitudes variables as reflective blocks (Bollen & Lennox, 1991; Diamantopoulos & Siguaw, 2006; Menichelli et al., 2014). As a reflective block, the manifest variables (MVs) in the block are assumed to measure the same unique underlying concept (Vinzi, Trinchera, & Amato, 2010). The full PLS-PM model requires in this case that all blocks are uni-dimensional. Checking for uni-dimensionality with Cronbach's alpha requires the MVs to be positively correlated (Tenenhaus et al., 2005). For these reasons, some MVs should be replaced by its opposite form. In the *mental hunger* block, for example, the item "Rate your current feeling of fullness" indicated the negative correlation with its own block. The solution to fix this problem was to change the sign of this item so that instead of "feeling of fullness" it reflected "feeling of hunger". Similarly, for each block, the correlations of MVs and responding block were considered, then the signs of MVs were changed if necessary before calculating Cronbach's alpha.

Data comprised different blocks; consumer characteristics: *hunger and fullness*, *attitudes toward healthfulness*, *attitudes toward taste*; and product characteristics: *liking*, *expected satiation*, *expected satiety* and *portion-size selection*. These blocks should be divided into separate blocks with the goal of controlling the uni-dimensionality issues (as required by PLS-PM).

For the *hunger and fullness question*, each factor (i.e. mental Hunger, mental Fullness, physical Hunger, physical Fullness) measured only one aspect of hunger and fullness feelings (Karalus & Vickers, 2016). Similarly, each factor in *attitudes toward healthfulness of foods*, *attitudes toward taste* measured one aspect of consumer attitudes (Roininen et al., 1999).

PCA (Mardia, Kent, & Bibby, 1979) was applied to each product related block (i.e. liking, satiation, satiety and portion) using double centered data, the scores and loadings were computed. The rows now represent the consumers as described above. For standard PCA of consumer data (i.e. in preference mapping studies), mean centering for each consumer will usually be done, meaning that the additive differences between consumers (i.e. different use of the scale) have been eliminated (Næs, Brockhoff, & Tomic, 2010). Since each column is mean centered the standard way in PLS-PM, this leads to double centered data (Menichelli et al., 2014), i.e. data is mean centered across products and across consumers for each combination of sample *i* and consumer *j*. By doing so, both the difference in level between the consumers and the average differences between the products were eliminated. This means that the PCA will focus on how the different consumer relate to the average consumer for each product (Endrizzi, Gasperi, Rødbotten, & Næs, 2014; Endrizzi, Menichelli, Johansen, Olsen, & Næs, 2011). This approach is supported by the fact that for the PCA done without double centering, the first component represented only different use of the scale with all consumers lying on one side of the first component.

The PCA revealed that all product blocks were multi-dimensional. An approach based on interpreting the principal components scores and using them as separate blocks was then applied (see also Menichelli et al., 2014). Two components described most of the interesting information for each data block. By doing so, instead of the eight values responding to the eight samples for each consumer rating (i.e. liking, satiation, satiety, portion size), the scores from two PCA components were used as input (in separate blocks) to the prediction model for each block.

In order to examine the meanings of PCA dimensions, sensory attributes from CATA questionnaire were treated as supplementary observations. This was achieved by projecting the frequencies of sensory attributes on the PCA space; that is, the factor scores of the supplementary observations were not used to compute the principal components (Abdi & Williams, 2010; Næs, Brockhoff, & Tomic, 2010).

The original blocks and separate blocks used in PLS path modelling are described in Table 2.

Table 2
The blocks used in the prediction model.

Original block	Block in PLS-PM model	Abbreviation of block
Hunger and fullness	Mental hunger	mHunger
	Mental fullness	mFull
	Physical hunger	pHunger
	Physical fullness	pFull
Attitudes toward healthfulness	General health interest	general
	Light product interest	light
	Natural product interest	natural
Attitudes toward taste	Craving for sweet food	craving
	Using food as a reward	reward
	Pleasure	pleasure
Liking	Liking for dimension V	LikingV
	Liking for dimension P	LikingP
Expected satiation	Satiation for dimension V	SatiationV
	Satiation for dimension P	SatiationP
Expected satiety	Satiety for dimension V	SatietyV
	Satiety for dimension P	SatietyP
Ideal portion-size	Portion for dimension V	PortionV
	Portion for dimension P	PortionP

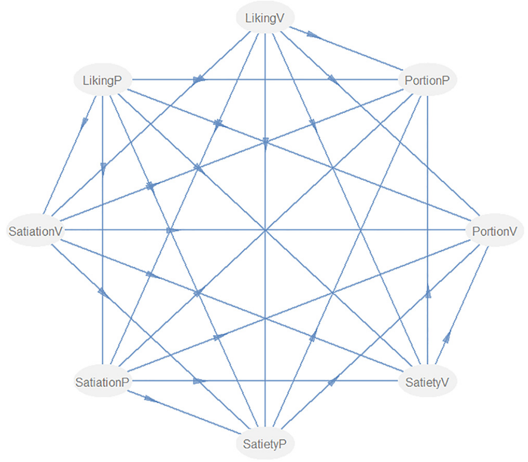

Fig. 3. Path model of product related variables (*prod* model). *V and P were the notation of viscosity and particle-size dimension, respectively.*

2.3.2.3. The path model used. The path model given main attention in this paper is given in Fig. 3. The blocks were introduced according to the theorized relation between them. The relationship between liking and satiation, satiety as well as portion was established with respect to the sequence of cognitive and physiological processes when people consume a food product (Blundell et al., 2010). Based on that, liking was incorporated before satiation (mostly influenced by sensory attributes) and satiety (imparted by sensory attributes, cognitive, post-ingestive and post-absorptive). These expectations will be incorporated into the framework to determine portion selection.

In the secondary path model comprising all blocks, all questionnaire variables were used as input to the product related variables and the product related variables were introduced according to the theorized relation between them as discussed above. The consumer related variables (questionnaire) were assumed to influence consumer expectations.

2.3.2.4. Simplifying the model. In order to simplify the path model, a reduction was tried by testing each of the links by bootstrap based t-tests. Different sizes of p-values (0.1, 0.05 and 0.01) were tested to validate the stability of the reduction.

The models should be compared on criteria such as the strength of the relations between variables as well as direct and indirect effects. By definition, the direct effect was that influence of one variable on another that was unmediated by any other variables in a path model; the indirect effects of a variable were mediated by at least one intervening variable (Bollen, 1989; Kaplan, 2009). For the models, main emphasis was given to two components in this case, but the third component was also given some attention.

All data were collected with EyeQuestion (Logic8 BV, The Netherlands) and analyses were carried out using R software (R Core Team, 2018). The packages *plspm* (Sanchez, Trinchera, & Russolillo, 2017) and *semPLS* (Monecke & Leisch, 2012) were used for performing PLS path modelling.

3. Results

First of all, the results from the unbalanced nested ANOVA (Table 3) revealed that while *sample* was significant for liking, satiation, satiety and portion, the *MB group* was not significant at test level of 0.05.

However, it is important to see that the interaction product:MB was statistically significant for satiation, while it was not for the rest of consumer expectations, suggesting that mouth behavior plays a role in the expectations of satiation. The interaction indicates that consumers rated the expected satiation of a product depending on the MB group they belonged (Fig. 4). It is reasonable as *chewers* and *crunchers* on one side and *smooshers* on the other, fall into two major modes of mouth actions which seem to have separated people by their primary mouth behavior, preferring to use their teeth to break down foods vs manipulating it between the tongue and roof of the mouth respectively (Jeltema et al., 2015, 2016). In particular, *chewers* and *crunchers* differentiated between two groups of products: P2, P4, P6, P8 (thick samples) in high satiation and P1, P3, P5, P7 (thin samples) expected as lower in satiation. *Smooshers* however, tended to classify products into three groups in descending order of satiation from P2, P4, P6, P8 (thick samples) and then discriminating into two groups of these samples, depending on the particle size and flavour level (P5, P7 and then P1, P3). This may suggest that the managing of the samples between the tongue and the upper palate could make them more aware of the flavour and particle size as drivers of satiation in thinner samples. The implication of MB in the model will be further commented in the discussion section.

Table 3
ANOVA results (p-values) for each consumer expectation.

	Liking	Satiation	Satiety	Portion
product	< 0.001	< 0.001	< 0.001	< 0.001
MB	0.604	0.969	0.269	0.184
product:MB	0.412	0.008	0.996	0.882

3.1. PCA for individual product blocks

Fig. 5 points out that the samples were separated on the first PC space for liking (a) and expected satiety (b). On the first dimension, samples were split into two groups regarding to liking, with P1, P5, P7 in one group and P2, P4, P6, P8 in the other. Then the second dimension separated samples into two groups, P3, P4, P7, P8 on the top and P1, P2, P5, P6 at the bottom of the dimension. It can be noted that the same structure was relevant for liking, satiation and portion (data not shown for these last two), but not for satiety. In that case, the importance of the first two dimensions was interchanged. The first dimension separated samples into two groups of P4, P7, P8 and P1, P2, P3, P5, P6 (Fig. 5b). To understand this, one could look at these results together with the sensory attributes as described by consumer in the CATA question.

For liking (Fig. 6a), the first dimension was explained by viscosity with *Thick* and *Liquid* attributes located in the opposite sides, whereas the second dimension was characterized by the particle-size (*Sandy* and *Pieces*). Similarly, these characterizations were observed for satiation and portion size. As described above, for satiety, the position of the two dimensions was switched, the first dimension became the particle-size dimension and the second was the viscosity dimension (Fig. 6b). These results are reasonable with regard to the design of experiment (viscosity, particle-size and flavour intensity variables). More specifically, the samples P1, P3, P5, P7 were designed as thin viscosity, the samples P2, P4, P6, P8 were thick in viscosity; oat flour was added to the samples P3, P4, P7, P8 and oat flakes to the samples P1, P2, P5, P6.

The third dimension was also taken into consideration. For liking and portion size, it was described as the Sweet-Sour dimension, whereas for satiation and satiety, it was the Sandy-Pieces dimension. The separation of sensory attributes was however not relevant enough to have a clear interpretation or naming of the third dimension. From these results, instead of eight ratings in response to eight samples, the three dimensions, the so-called *viscosity* (V), *particle-size* (P) and the *third dimension*, will be used for the analyses throughout the paper.

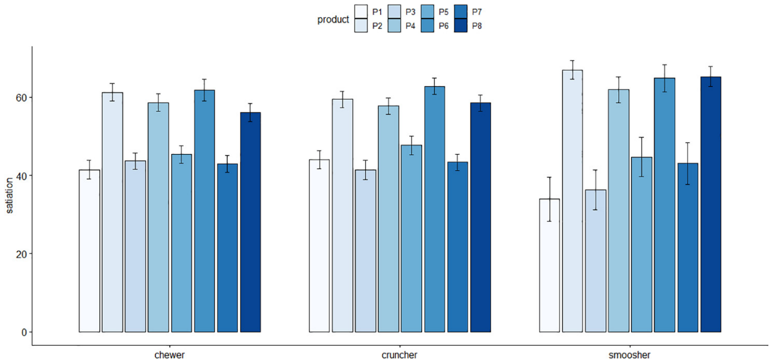

Fig. 4. Interaction plot (product:MB) for expected satiation.

3.2. The prediction model

3.2.1. The model of product related variables only (prod model, 2 first PCA components)

To simplify the graphical interpretation task, and due to the excessive number of variables in the data set, the focus will be on the block of product related variables. At first, the full prod model was considered, and then the stability of model was investigated by comparing some reduced models responding to different p-values (0.1, 0.05 and 0.01). Afterwards, the specific model should be chosen to explain the main relations between variables.

The relations between product variables in the full model were displayed in Fig. 7; some relations were well defined, however, other relations with the path coefficients, i.e. direct effects, were equal to zero and almost zero (*LikingV-SatietyP*, *LikingV-PortionP*, *SatiationP-PortionP* and *SatietyV-PortionV*). These relations should be eliminated from the model for obtaining the more stable models.

The validation of the model simplification pointed out that the main relations between product related variables were stable with different p-values (0.1, 0.05, 0.01). In other words, the reduced models had some slight changes, but the main trend was not changed. The significant relations decreased in the reduced models with respect to p-values. Comparing to the reduced models of p-value 0.1, in the reduced model of p-value 0.05, the relations *LikingV-SatiationP*, *LikingP-SatietyP*, *SatiationP-PortionV* were eliminated. In the light of this trend, in the reduced model of p-value 0.01, the relations *SatiationV-PortionP*, *LikingP-SatiationV*, *SatiationP-SatietyV* continued to be removed. Apart from *LikingP-SatietyP*, all eliminated relations did not display the relations of consumer expectations on the specific dimension (*viscosity* or *particle-size*). That is possible explanation why these relations were not stable with different p-values.

In addition to the path coefficients, the explained variances of endogenous blocks were considered (Table 4). It was not surprising that these blocks were explained similarly for models with different p-values. Among those, *PortionP* was the most explained block (R2: 0.48–0.50), whereas *SatiationP* was the least explained one (R2: 0.09 – 0.11). These results supported the above findings in which the product models were stable with different p-values.

Without loss of generality, the reduced model of p-value 0.1 was selected to account for the relations between product variables. The path diagram was depicted in Fig. 8 and the direct/indirect effects were summarized in Table 5. In the model, liking had positive and strong effects on portion with the path coefficients of 0.46 and 0.71 for *viscosity* and *particle-size* dimensions, respectively. Accordingly, liking was a good predictor for satiation and satiety. It is noteworthy that while liking directly influenced satiation (*LikingV-SatiationV*: 0.30, *LikingP-SatiationP*: 0.37), it did not contribute directly to satiety for each dimension. The effect liking-satiety was indirect through satiation, that is, liking influenced satiation, which in turn, imparted satiety (*LikingV-SatiationV-SatietyV*: 0.13, *LikingP-SatiationP-SatietyP*: 0.15). On this relation, it is interesting to find that *LikingV* had indirect and positive effect on *SatietyV*, and on the opposite side, *LikingP* had direct and negative effect on *SatietyV* (−0.29). To sum up, the strongest indirect relation was the relation between liking and satiety; the direct effects confirmed the strong relations of liking-portion, liking-satiation, satiation-satiety and especially *LikingP-SatietyV*.

3.2.2. The model with three components

In this part, models were built taking into account three dimensions of viscosity, particle-size and the third dimension. Then, the

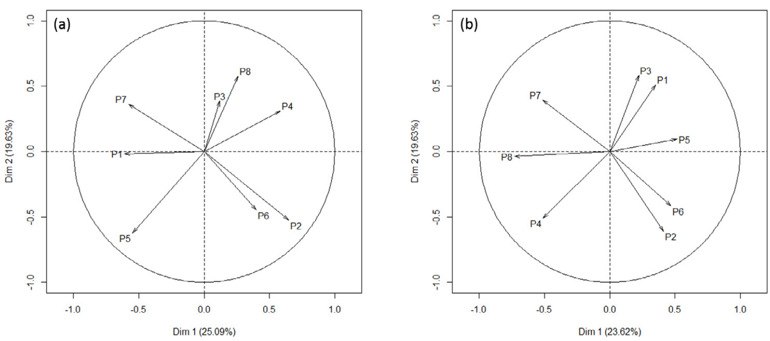

Fig. 5. PCA on double-centered data for Liking (a); Expected satiety (b).

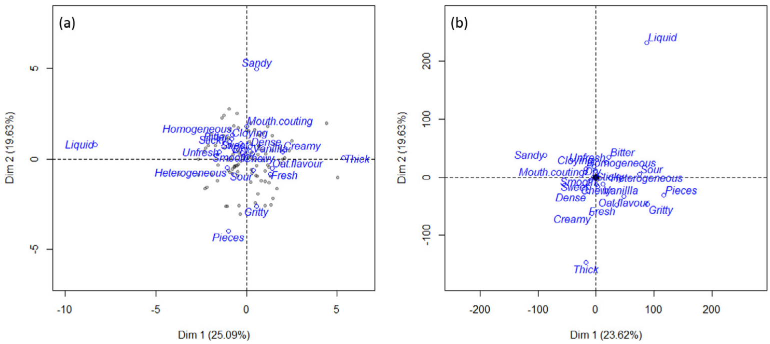

Fig. 6. CATA attributes profiled in the PCA space for Liking (a); Expected satiety (b).

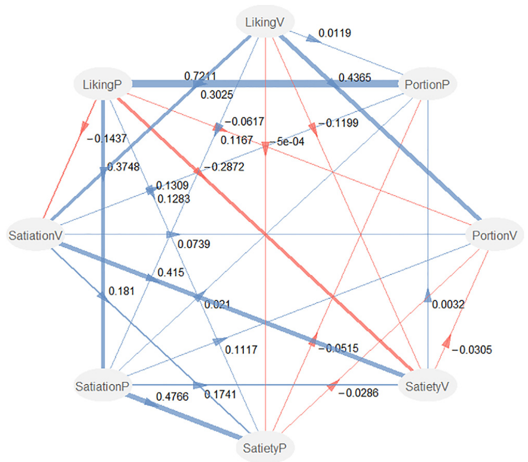

Fig. 7. Path diagram for the full *prod* model. *The 'blue' lines stood for the positive relations, the 'red' lines dedicated for negative relations, the thickness of the lines indicated the strengths of the relations and the numeric values together lines as the path coefficients (direct effects) between variables. V and P were the notation of viscosity and particle-size dimension, respectively.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

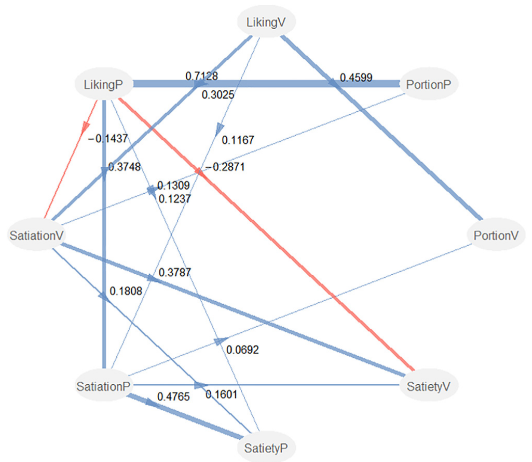

Fig. 8. Path diagram for the reduced *prod* model with p-values of 0.1.

Table 4
R2 of product models with different p-values.

	Model *full*	Model *pval-0.1*	Model *pval-0.05*	Model *pval-0.01*
SatiationV	0.11	0.11	0.11	0.09
SatiationP	0.15	0.15	0.14	0.14
SatietyV	0.26	0.25	0.25	0.23
SatietyP	0.32	0.32	0.30	0.30
PortionV	0.23	0.22	0.22	0.22
PortionP	0.50	0.50	0.50	0.48

comparisons between the models with different p-values. The results showed that the reduced model with p-value 0.05 seemed to be the optimal model because it kept enough information for interpretation with less complexity. For *viscosity* and *particle-size* dimension, the relations were still liking-portion and liking-satiation-satiety, for the third dimension, however, there were some interactions. The third dimension seemed to be the mixture of viscosity and particle-size dimensions; that is, it played the role of viscosity dimension in some relations, and particle-size in other relations. Thus, including the third dimension in the model was not relevant for interpretation and more difficult to understand. These results supported for the decision for which only two dimensions (i.e. *viscosity* and *particle-size*) should be used in the model.

Table 5
Direct and indirect effects of reduced model of p-value 0.1.

Relationships	Direct effect	Indirect effect
LikingP – SatietyV	−0.29	0.01
LikingP – SatiationV	−0.14	0.00
LikingV – SatietyP	0.00	0.11
LikingV – SatietyV	0.00	0.13
LikingV – PortionP	0.00	0.04
LikingP – PortionV	0.00	0.03
SatiationP – PortionV	0.07	0.00
LikingV – SatiationP	0.12	0.00
SatiationV – PortionP	0.12	0.00
LikingP – SatietyP	0.13	0.15
SatiationP – SatietyV	0.16	0.00
SatiationV – SatietyP	0.18	0.00
LikingV – SatiationV	0.30	0.00
LikingP – SatiationP	0.37	0.00
SatiationV – SatietyV	0.38	0.00
LikingV – PortionV	0.46	0.01
SatiationP – SatietyP	0.48	0.00
LikingP – PortionP	0.71	−0.02

3.2.3. The model of consumer and product variables (con-prod model)

The relations in the *con-prod* model often followed the specific dimensions, i.e. particle-size (P) and viscosity (V) dimension. In other words, the direct relations of liking-portion and indirect relation of liking-satiation-satiety were relevant for each dimension. The stability of this model was also investigated with different p-values. The results (data not shown here) revealed that the relations between product variables were stable and similar to the common pattern of the *prod* model described previously, whereas those of consumer variables were quite sensitive with different p-values. In order to eliminate some non-significant relationships and keep enough information for interpretation, the p-value of 0.05 was chosen for the reduced model. In general lines, hunger and fullness feelings as measured by the questionnaires influenced both liking and satiation/satiety as measured for the products. *Physical hunger* had a negative effect on *liking*; *mental fullness* negatively imparted *satiation* and positively imparted *satiety*. For variables related to consumer attitudes towards healthfulness and taste of food, they only influenced liking.

3.3. The influence of individual differences on the predicted model

The results of this part of the study looked into the effects of the variable *eating-style* on the prediction model. Based on consumers' mouth behaviors as classified with the JBMB™ typing tool, consumers can be classified into four major groups, however, in the present work consumers fell into three groups only: *Chewer*, *Cruncher* and *Smoosher*, no *Sucker* was identified by the data. The path diagrams of these three groups are depicted in Fig. 9. Basically, a similar model was obtained in general lines to predict portion for the three groups of consumers. Nevertheless, there was noteworthy difference in *LikingV-PortionV*. While the relation was positive and strong for *Chewers* (0.44) and *Crunchers* (0.65), it seemed to be weak, and if any, negative (−0.11) for *Smooshers*. Particularly, *Smooshers* might use only *particle-size* for predicting portion; as a strong relation *LikingP-PortionP* (0.68) was observed in Fig. 9c. The results are in agreement with previous studies (Jeltema et al., 2015, 2016), stating that consumers used different strategies to manipulate foods and this influenced their expectations. In this study, *Chewers* and *Crunchers* seemed to use both two sensory dimensions (*viscosity* and *particle-size*) for estimating the *Portion*, meanwhile *Smooshers* used *particle-size* only.

4. Discussion

4.1. The relation between liking and satiety

The prod model (Fig. 7) displays the general framework which describes the relationships between consumer expectations. This model pointed out that an increase in liking leads to an increase in prospective portion size (both when driven by particle size or by viscosity). In addition, a higher liking could produce greater satiety as a consequence of a greater satiation. It is compatible with the results of the previous studies (De Graaf, De Jong, & Lambers, 1999; Johnson & Vickers, 1992; Yeomans, 1996). These authors studied the effect of liking on satiation, highlighting that the absence of the effect of liking on subsequent satiety was clear. Note that the results from the previous studies have been achieved in terms of direct relations only. In the present study, both direct and indirect effects are interpreted. When the interactions are included in the model, the interpretation becomes more complicated. Different dimensions of liking resulted in different effects on satiety; *LikingP-SatietyV* with negative effect and *LikingV-SaietyV* with positive effect. Note that the latter is indirect effect through *SatiationV*, which is obtained by multiplying the path coefficient of *LikingV* on *SatiationV* with the path coefficient of *SatiationV* on *SatietyV*.

From the sensory perspective, sensory perception is not a single event but a dynamic process with a series of events (Labbe, Schlich, Pineau, Gilbert, & Martin, 2009). The relation between these sensations and sensory-specific satiation/satiety are not static during consumption (Karen, 2004; Morell, Fiszman, Varela, & Hernando, 2014). In a previous study done on the same yoghurt samples of the present study, the product trajectories, highlighted by dynamic profiling via TCATA, pointed out the common pattern in temporal profiles in which the samples were first separated by *viscosity* and then by *particle-size* (Nguyen et al., 2018). This would support the hypothesis of a sequential assessment of liking linked to the sequential perception from viscosity (*LikingV*) to particle-size (*LikingP*). In other words, *this would highlight the temporal dimension of liking assessment, linked to the different* stages of the dynamic sensory perception of texture.

In the results, *viscosity* and *particle-size* have been interpreted as two orthogonal dimensions on the PCA space (Fig. 6); however, from a perceptual point of view, these properties can interact during the oral processing. Considering the rheology of a suspension (as the yogurt model here), if the total mass of particles in a suspension is kept constant but the particle size of the is reduced, then viscosity in the system would increase (Hardacre, Lentle, Yap, & Monro, 2018; Mueller, Llewellin, & Mader, 2010; Tarancón, Hernández, Salvador, & Sanz, 2015). In the present study, a decrease in particle size of the oat flakes would contribute to an increase in viscosity in the yoghurt samples. For that reason, *LikingP* might play a role of "*-LikingV*". In the prediction model, the relation of *LikingV-SatietyV* has a positive effect, meaning that, if consumers like a sample with thick viscosity, they will perceive it as more satiating as well. Consequently, *LikingP* has negative influence on *SatietyV*, as a yogurt with bigger particles could be less viscous, and consequently perceived as less satiating.

In present years, many studies have investigated the role of viscosity

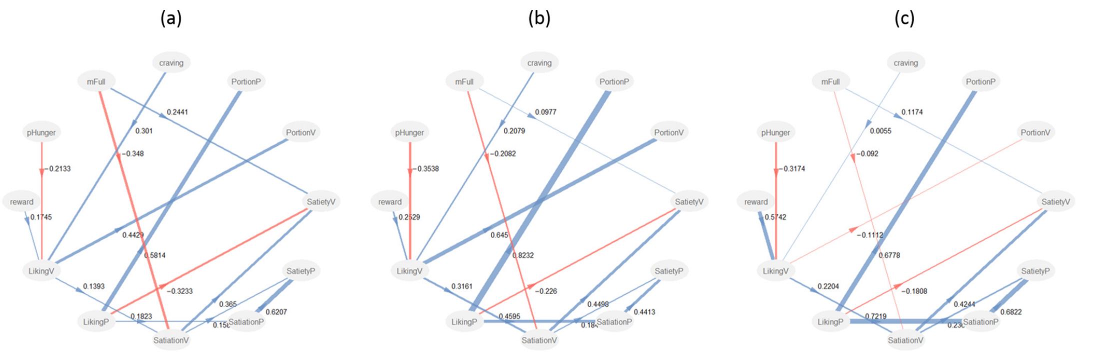

Fig. 9. The path diagram for consumer-product model with p-value of 0.05 for Chewers (a), *Crunchers* (b) and *Smooshers* (c).

and food particles on expectations of satiation and satiety. These studies stated that both viscosity and solid food particles have been reported as modulators of expectations about satiety in which an increase in the perceived thickness was positively correlated with the expected satiation, and more solid foods may evoke increased satiety (Hogenkamp & Schiöth, 2013; Hogenkamp et al., 2011; Marcano, Morales, Vélez-Ruiz, & Fiszman, 2015). The explanations based on the oro-sensory exposure; in particular, higher viscosity in a food leads to longer oro-sensory stimulation (Mars, Hogenkamp, Gosses, Stafleu, & De Graaf, 2009) and more solid products require more labor and time in the mouth, causing longer oro-sensory exposure (Hogenkamp & Schiöth, 2013). As a consequence, an increase in oral processing may result in higher satiety (Forde, van Kuijk, Thaler, de Graaf, & Martin, 2013; Hogenkamp & Schiöth, 2013). On the contrary, Tarrega and colleagues have shown that a more viscous product base increased the mean expected satiation regardless of the food particle added (Tarrega, Marcano, & Fiszman, 2016). Unlike to those studies, the present study indicated that while viscosity positively imparted satiety, food particle negatively influenced satiety; that is, bigger particles lead to less satiating perception.

This result is not observed for *SatietyP*. The possible reason is that the "particle size – viscosity" relation is only one direction from particle-size to viscosity, not in the opposite direction. Apart from the viscosity effect of the reduced particle size, other sensory perceptions related to the oral process might be affecting satiety perception in different directions. For example, the effect of the small particles might have in the eating rate; having very small particles in the mouth can require longer work with the tongue to being able to swallow the product. This sandy perception can in turn affect liking in different ways, depending on the preferences and mouth behaviour.

4.2. The relation between consumer characteristics and consumer expectations

Focusing on expected satiety, higher mental fullness (*mFull*) scores predicted larger decreases in viscosity related satiation (*SatiationV*). The finding is in accordance with Mattes and colleagues, pointing out that a higher expected satiety led to decrease in hunger and increase in fullness immediately after consuming the food (Mattes & Vickers, 2018). As opposed to satiety, mental fullness (*mFull*) had negative effect on satiation (*mFull* scores predicted larger increases in viscosity related satiety – *SatietyV*), meaning that the feeling of mental fullness might reduce consumers' satiation.

While mental fullness significantly influenced satiation and satiety expectation, physical hunger (*pHunger*) influenced liking; in particular, liking related to viscosity (*LikingV*). When consumers rated a higher physical hunger, they tended to dislike yogurts that were thicker. However, *pHunger* was not the only predictor, *craving* and *reward* also contributed to the changes of *LikingV*. The strengths of these relations (*craving-LikingV*, *reward-LikingV*) are similar and positive. That suggests that liking should be considered as complex concept which is imparted by several factors, at least in the present study, such as hunger and fullness feelings and attitudes to healthiness, and taste of foods.

4.3. Determining number of components

In order to maintain the uni-dimentionality of data blocks in the PLS-PM approach, PCA was applied on each data block and then only the first two components are selected for subsequent analyses. In the present study, the selection was not very difficult due to the fact that the samples have been formulated from a design of experiment of viscosity, particle-size and flavour intensity variables. However, when more complex samples with a wide range of sensory perceptions were used, the selection of the number of dimensions in the model could be indeed a difficult task in itself. This problem could be solved with some other approaches such as SO-PLS path modelling (Næs, Tomic, Mevik, & Martens, 2011) or Path-ComDim (Cariou, Qannari, Rutledge, & Vigneau, 2018). These approaches can be used for any dimensionality of the blocks of variables. Research work is needed to further compare these approaches to deeper understand advantages and limitations.

5. Conclusions

This paper has shed some light on the question of whether "quality can replace quantity" although the answer is not straightforward. With the model obtained by PLS-PM, liking played an important role in predicting portion selection. More specifically, a higher liking meant a bigger portion selection for the semisolid system under study. Besides that, satiation and satiety could be predicted from liking directly and indirectly, the understanding of the implications, however, needs to be considered carefully due to the dynamic and multiparametric nature of these expectations.

The present study suggests that PLS-PM could be an appropriate tool to explain the relationships between consumer attitudes, product assessment and expectations. In this case study, consumer expectations of liking, satiation, satiety, and prospective portion were clearly two dimensional and it has been shown how it can be interpreted. But when the sensory dimensions underlying those expectations become more complex, resulting in more dimensions, the interpretation of consumer expectations within such a complex model might not be obtained easily and explicitly.

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PAPER 4

(in preparation)

SO-PLS path modelling as holistic approach to explore relations between consumer liking, expectations of satiety and portion size selection

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Abstract

To understand consumers' portion size selection, a holistic approach is required in which several aspects of consumer expectations could be considered simultaneously (i.e. liking, expected satiety, expected satiation). In this sense, PLS path modelling (PLS-PM) has been found as a good tool to model this relation, but this approach faces some issues regarding the assumption of uni-dimensionality of consumers' data blocks. SO-PLS path modelling (SO-PLS-PM) has been proposed as an alternative approach to handle the uni-dimensionality issue and to explain the relations between original data blocks without any preprocessing of the data. In this context, this study aims at comparing the results obtained by PLS-PM and SO-PLS-PM using two data sets with different complexities. Two data sets (yoghurt and biscuit case studies) were collected in two consumer tests. Consumers were asked to taste products, and then rate their liking, expected satiation, expected satiety and prospective portion size.

Results indicated that the two approaches (PLS-PM and SO-PLS-PM) highlighted the same main trends for the less complex data (yoghurt samples): liking was the essential driver of satiation and portion; while satiation mainly predicted satiety. For the more complex data set (biscuit samples), the PLS-PM model was difficult to interpret, whereas it was well explained by SO-PLS-PM. The main difference was the relation *Liking-Satiation* and *Satiety-Portion* which were significant in PLS-PM, but not in SO-PLS-PM. Additionally, with different definitions of direct, indirect and total effects, SO-PLS-PM also demonstrated some advantages over PLS-PM.

Keywords: *liking; satiety; consumer expectations; path modelling; PLS; SO-PLS; uni-dimensionality*

1. Introduction

Consumer expectations in an integrated framework

Obesity has become an international public health issue that affects the quality of life (Kopelman, 2000; World Health Organization, 2003). In this context, energy-reduced foods have been demonstrated as a potential solution in some studies (Buckland, Bach, & Serra-Majem, 2008; Du & Feskens, 2010; Jebb, 2007; Maskarinec et al., 2006; van Dam & Seidell, 2007). It emphasizes the consumption of low energy dense foods to meet nutrient needs without exceeding energy requirements (Nicklas et al., 2008). The sensory experience of eating is an important determinant of food intake control, often attributed to the positive hedonic response associated with certain sensory cues (McCrickerd & Forde, 2016). However, palatability is just one aspect that influences food intake or portion size selection (Cooke & Wardle, 2005; Yeomans, 2007; Yeomans, Blundell, & Leshem, 2004); other aspects such as expected satiation or satiety have been found to be significantly correlated with portion size selection or food intake (Brunstrom & Rogers, 2009; Brunstrom & Shakeshaft, 2009). Although, consumer expectations (i.e. liking, satiation, satiety, portion) have been identified in practice, very few studies considered simultaneously all these expectations; therefore, one potential route would be to combine all these blocks of data in an integrated framework and built a predictive model to interpret their relations (Guillocheau et al., 2018). This approach results in a composite dataset in which the portion ($\boldsymbol{X_4}$) is explained by several meaningful blocks, i.e. liking ($\boldsymbol{X_1}$), satiation ($\boldsymbol{X_2}$) and satiety ($\boldsymbol{X_3}$) using the same individuals.

Multiblock modelling

This kind of data should be subjected to multiblock modeling methods which provide valuable tools to investigate the relationships among blocks of data and highlight which blocks and which variables are determinant in explaining the variables in predicted block (Bougeard, Qannari, & Rose, 2011). These approaches have been widely used in the field of process monitoring (Kourti, 2003; Qin, Valle, & Piovoso, 2001; Westerhuis & Coenegracht, 1999), chemometrics (Kohonen et al., 2008) and sensometrics (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005).

In this paper, we will focus on methods based on partial least squares (PLS). Within the family of methods pertaining to PLS, there are several kinds of analyses such as

Multiblock Partial Least Squares (MB-PLS) and Structural Equation Modelling (SEM) (also called Path modelling, PM) depending on which path diagram is considered (Höskuldsson, 2008). Considering the framework of consumer expectations where liking, satiation and satiety influence each other and together they influence portion size, we will in this paper focus on a PM approach.

Path modelling

PM involves the specification and testing of the relationships between variables that are observed (indicators/ manifest variables) and unobserved (latent variables). The two most used ways of handling this type of data are covariance-based (CB-PM) and component-based (PLS-PM) methods (Fornell & Bookstein, 1982; Jöreskog & Wold, 1982; Rigdon, 2012; Tenenhaus, 2008). These two approaches to PM differ greatly in their underlying philosophy and estimation objectives (Tenenhaus et al., 2005). More specifically, CB-PM focuses on the model's theoretically established relationships and aims at minimizing the difference between the model implied covariance matrix and the sample covariance matrix. In contrast, PLS-PM is a prediction-oriented approach that focuses on endogenous target constructs in the model and aims at maximizing their explained variance (Hair, Ringle, & Sarstedt, 2012). They are different but complementary statistical methods for PM, whereby the advantages of the one method are the disadvantages of the other (Hair, Sarstedt, Pieper, & Ringle, 2012; Jöreskog & Wold, 1982; Tenenhaus, 2008). Herein, we restrict ourselves to the PLS-PM approach to explore the relations in the framework of consumer expectations.

Some issues in PLS-PM

Basically, PLS-PM is a two-step method, iterating between estimating the inner relations among the latent variables and the relations between the latent and manifest variables block-wise (Wold, 1980). A large number of important applications have been developed based on this method, but it also suffers from a number of challenges (Tenenhaus, 2008).

Firstly, PLS-PM does not generally solve a global optimization problem for parameter estimation, indicating that there exists no single criterion which is consistently minimized or maximized to determine model parameter estimates (Fornell & Bookstein, 1982; Jöreskog & Wold, 1982; Wold, 1982). For one of the modes, however, it has been shown that the optimization can be considered as a maximization of a sum of covariance, but this is not so easy to interpret in practice (Hanafi, 2007). Secondly, the method is not invariant to the between blocks scaling, meaning that prior to analysis one must decide on a proper scaling of the blocks.

The most serious challenge of PLS-PM is, however, the assumption of uni-dimensionality of the reflective mode in the measurement model (Tenenhaus et al., 2005; Vinzi, Trinchera, & Amato, 2010). Specifically, if the measurement model is reflective, then its manifest (observed) variables are assumed to measure a unique underlying concept. However, it can be violated in sensory and consumer studies due to the multi-dimensionality of nature. Very often, product properties and consumer characteristics are described multi-dimensionally (Menichelli, Almøy, Tomic, Olsen, & Næs, 2014), leading to multi-dimensional blocks in the data set. One possible solution is to split the original block into sub-blocks of uni-dimensionality; however, it is not a straightforward task to decide the number of sub-blocks, especially in cases of complex products (Nguyen, Næs, Almøy, & Varela, 2018). Other approaches can be found in (Martens, Tenenhaus, Vinzi, & Martens, 2007; Romano, Tomic, Liland, Smilde, & Næs, 2018).

An alternative approach to path modelling

As alternative and more exploratory approach based on the Sequential and Orthogonalized PLS for multiblock regression analysis (here named SO-PLS-PM) was put forward in (Menichelli, Almøy, et al., 2014; T. Næs, Tomic, Mevik, & Martens, 2011; Romano et al., 2018). The method splits the estimation up into separate multi-block regression models for each endogenous block (Menichelli, Almøy, et al., 2014; T. Næs et al., 2011). The method easily handles different number of variables in the blocks and different underlying dimensionality. In addition, it is invariant to the relative scaling of the blocks, meaning that no preprocessing is needed for balancing the influence of the blocks. The method also possesses many additional features to be discussed below. In SO-PLS-PM, the relations between variables are explained by Principal components of predictions (PCP) (Langsrud & Næs, 2003).

The focus of the present paper is on comparing PLS-PM and SO-PLS-PM empirically on two datasets with different complexity of product dimensions. Special focus will be on how to handle the uni-dimensionality issue in a situation with clearly multidimensional blocks. In particular, a proposal that was put forward in (Menichelli, Hersleth, Almøy, & Næs, 2014) and (Nguyen, Næs, Almøy, et al., 2018) based on splitting according to principal component analysis is tested. Results are summarized, and advantages and disadvantages of these two approaches are discussed.

2. Methodology

PLS-PM and SO-PLS-PM are compared in this work based on modelling consumer data from two case studies, one on yoghurt and another on biscuit. In the next sections the statistical approach is described first, followed by the practical details of the data collection in both case studies.

2.1. PLS path modelling (PLS-PM)

In this paper, we will consider relations between J blocks, $\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots, \boldsymbol{X_J}$ of data. We let k_j be the number of columns in block j and n will be the number of rows.

In general, the observed variables (i.e. manifest variables MVs) in individual blocks are very numerous and inter-correlated. Thus, direct fitting of data blocks to each other by, for instance, least squares (LS) becomes impossible. The principle behind PLS-PM is that an iterative algorithm estimates the relationships among blocks of observed variables (indicators or manifest variables (MV)), through the construction of non-observed variables (i.e. Latent variables LVs) which describe the main variability in the MVs. Simple and multiple regressions were applied to estimate the relationships between these variables (Vinzi, Chin, Henseler, & Wang, 2010). In this paper, we will only consider the reflective mode where all manifest variables in block j are considered linear functions of the corresponding latent variables.

The PLS estimation proceeds into the following stages. First, an iterative procedure estimates the weights and the LVs. Second, the LVs estimated in the first stage provide regressors for estimating the path coefficients of the model by OLS regressions (Tenenhaus et al., 2005; Wold, 1980).

- Stage 1: Estimate weights for indicators and scores of LVs

Each LV score $\boldsymbol{Y_j}$ in block j is calculated as a weighted sum of their indicators (Eq. 1).

$$\widehat{LV}_j = Y_j = \sum_k \boldsymbol{w_{jk}} \boldsymbol{x_{jk}} \tag{1}$$

where summation is over $k = 1, \ldots, k_j$.

The algorithm begins with arbitrary initial outer weights $\boldsymbol{w_{jk}}$; for simplicity, all weights can be initialized equal to 1. The initial LV scores are calculated (Eq. 1), and then applied to the estimation in the structural model. Here, a score of LV is re-calculated as the linear combination of its associated LVs.

$$Z_j = \sum_i \boldsymbol{e_{ij}} \boldsymbol{Y_i} \tag{2}$$

In this step (inner estimation), the inner weights $\boldsymbol{e_{ij}}$ are estimated using Centroid, Factor or Path schemes (Vinzi, Trinchera, et al., 2010). Then, the estimates Z_j are calculated based on Eq. 2.

Once the inner estimation is done, the estimates Z_j must then be considered in relation to the MVs. There are two ways to estimate the outer weights $\boldsymbol{w_{jk}}$: reflective (mode A) and formative (mode B). The former, which is the focus here, one simply regresses the individual $x's$ in block j onto the corresponding LV_j.

With updated outer weights $\boldsymbol{w_{jk}}$, the new iteration is continued. The sum of absolute changes in weights from one iteration to another (namely convergence) was recorded and compared with a threshold of 10^{-5}: if it falls below this threshold, the algorithm is terminated (Henseler, 2010; Wold, 1982).

- Stage 2: Estimate path coefficients of structural model

The LVs are related by a path of inner/structural relations. For the sake of simplicity, we dismiss the difference between exogenous and endogenous LVs, and express their relation as:

$$\boldsymbol{Y} = \boldsymbol{YB} + \boldsymbol{error} \tag{3}$$

with $\boldsymbol{Y}$ denotes the matrix of the LVs, both exogenous and endogenous; $\boldsymbol{B}$ represents the matrix of path coefficients. Elements of $\boldsymbol{B}$ equal 0 in cases of no relation between responding LVs (Monecke & Leisch, 2012).

With path coefficients, the effects (direct, indirect and total) are defined:

- Direct effects are given by path coefficients;
- Indirect effects are the influence of one block on another block by taking an indirect path calculated as the product of path coefficients;
- Total effects are the sum of both direct and indirect effects.

2.2. SO-PLS for path modelling (SO-PLS-PM)

The rationale behind SO-PLS-PM is to model each endogenous block separately as a function of all blocks that are input in it (Menichelli, Almøy, et al., 2014; T. Næs et al., 2011). The estimation method is the SO-PLS method which has several advantages to regular multiblock PLS (Jørgensen, Segtnan, Thyholt, & Næs, 2004; Tormod Næs, Tomic, Afseth, Segtnan, & Måge, 2013). The separate SO-PLS models (for endogenous blocks) can be interpreted in different ways using additional explained variance as new blocks are incorporated, the individual PLS models and the PCP method (Langsrud & Næs, 2003). The next part describes the main features of SO-PLS and PCP. After estimation of the basic SO-PLS models, an additional step of calculating direct, indirect and total effects of a block on another were proposed in (Romano et al., 2018), also based on the same estimation philosophy.

- SO-PLS for MB regression

Let us assume that data consists of three blocks in which $\boldsymbol{X_1}, \boldsymbol{X_2}$ as the explanatory blocks and $\boldsymbol{Y}$ as the response block. Their relations are described as follows:

$$\boldsymbol{Y} = \boldsymbol{X_1 B_1} + \boldsymbol{X_2 B_2} + \boldsymbol{error} \qquad (7)$$

where $\boldsymbol{B_1}, \boldsymbol{B_2}$ are regression coefficients.

The SO-PLS regression can be summarized by the following steps: the first step is to fix $\boldsymbol{Y}$ to $\boldsymbol{X_1}$ by PLS regression. The $\boldsymbol{X_2}$ is then orthogonalized with respect to the PLS scores $\boldsymbol{T_{X_1}}$ of $\boldsymbol{X_1}$ to obtain the orthogonalized $\boldsymbol{X_2^{orth}}$; in the second step, the original or deflated $\boldsymbol{Y}$ is fitted to $\boldsymbol{X_2^{orth}}$ using PLS regression, and the PLS scores $\boldsymbol{T_{X_2^{orth}}}$ are estimated; finally, $\boldsymbol{T_{X_1}}$ and $\boldsymbol{T_{X_2^{orth}}}$ are used as independent variables to predict response variable $\boldsymbol{Y}$ in a regular least squares (LS) regression. For more blocks, one simply repeats the same procedure.

Determining the number of components

As for regular regression, cross-validation is applied to determine the number of components to use for prediction and assess the quality of the predictor obtained, usually measured by the root mean square error of prediction (RMSEP) (H. Martens & Naes, 1992). In the SO-PLS regression, the optimal number of components can be selected using global or sequential optimization. The former does a full optimization of all blocks simultaneously. The latter, on the other hand, optimizes the number of components in the first block first, then in the second block with the components of the first block is fixed (T. Næs et al., 2011). In this paper, we will use the sequential approach since it fits best with the philosophy of using SO-PLS in a path modeling context.

Direct and indirect effects

The direct, indirect and total effects are also defined differently as compared to those in PLS-PM (Romano et al., 2018). Assume that block A imparts block C directly and indirectly through block B, the effects are defined in the following way: the total effect of block A on block B is the explained variance of B when regressed onto A; the direct effect of A on C is defined by how much of C that can be explained by A when orthogonalized with respect to B; the corresponding indirect effects are calculated as the differences between the total effects and the direct effects (see (Romano et al., 2018) for details).

- PCP

The PCP aims at providing information about which part of $\boldsymbol{Y}$ that can be predicted by which part of $\boldsymbol{X}$ (Langsrud & Næs, 2003). Let us calculate $\widehat{\boldsymbol{Y}}$ as predicted values of $\boldsymbol{Y}$ based on $\boldsymbol{X}$ using PLS regression. PCA is run on $\widehat{\boldsymbol{Y}}$, giving $\widehat{\boldsymbol{Y}} - \boldsymbol{scores}$ and $\widehat{\boldsymbol{Y}} - \boldsymbol{loadings}$. Since $\widehat{\boldsymbol{Y}}$ are linear functions of $\boldsymbol{X}$ and $\widehat{\boldsymbol{Y}} - \boldsymbol{scores}$ are linear functions of the $\boldsymbol{X}'s$, $\boldsymbol{X} - \boldsymbol{loadings}$ are obtained as the regression coefficients of these linear combinations (Menichelli, Almøy, et al., 2014; T. Næs et al., 2011).

3. Case studies

3.1. Yoghurt data

Eight yoghurt samples were prepared from a design of experiment (DOE) based on the same ingredients, only modifying the product texture by using different processing strategies, so as the samples would have the same calories and composition and these parameters would not influence satiety or satiation. The ingredients were commercial natural yogurt, cereal flakes and a combination of vanilla and high intensity sweetener. The parameters of the DOE were: yoghurt viscosity (thin/thick), cereal particle size (flakes/flour) and flavour intensity (low/optimal); see (Nguyen, Næs, & Varela, 2018) for details.

One hundred and one consumers were recruited for the test in the southeast area of Oslo from Nofima's consumer database. Consumers were asked to taste each sample and rate their liking on a Labelled Affective Magnitude (LAM) scale (Schutz & Cardello, 2001), expected satiation on a Satiety Labeled Intensity Magnitude (SLIM) scale (Cardello, Schutz, Lesher, & Merrill, 2005) and expected satiety on a 6-point scale from 1 = "hungry again at once" to 6 = "full for five hours or longer". For their ideal portion-size, they chose the amount they would consume as compared to the normal amount of commercial yoghurt product (they were showed an unbranded container). The portion-size scale, was one-third to 3-times compared to the normal portion size.

3.3. Biscuit data

Eight oat based biscuit samples were used in this study. Samples were prepared following the same idea as yoghurt samples, identical compositions but different textures. Two parameters of DOE were used: baking powder in two levels (with/without) and four levels of particle sizes (0.5mm, 2.0mm, small commercial flakes, big commercial flakes). A consumer test was carried out with one hundred and one consumers at IATA (Valencia, Spain). In this test, consumers tasted the samples and rated the same parameters as in the yoghurt case: liking on LAM scale, expected satiation on SLIM scale and expected satiety on 6-point scale. For portion size selection, they rated how many biscuits they would like to eat on a 6-point scale from "1 biscuit" and "6 or more biscuits".

3.3. Data analyses

The data was organized in a multiblock setting where $\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{X_4}$ responding to *liking*, *satiation*, *satiety* and *portion*. For each block, for instance *liking*, consumers represented the rows and liking ratings for the different samples represented the columns, i.e. each product has a separate column of liking values as suggested in (Menichelli, Hersleth, et al., 2014). Since data are centered for each consumer and block separately (each row), this leads to double-centered data since PLS regression is always run on columns centered data. (Endrizzi, Gasperi, Rødbotten, & Næs, 2014; Endrizzi, Menichelli, Johansen, Olsen, & Næs, 2011). Added to this, because these blocks were rated on different scales, standardization between blocks was applied by dividing each block according to the square root of the sum of squares (Frobenius norm). Note that this has no effect on the SO-PLS-PM, but is a requirement for PLS-

PM in which blocks were always standardized, and manifest variables were always centered and often standardized as well (Tenenhaus et al., 2005).

Each block of data (i.e. liking, satiation, satiety, portion) contained eight variables responding to the consumer ratings of the eight products. Considering liking, for instance, PCA was applied on this block and then the PCA loading plot indicated that this block was clearly two-dimensional. For that reason, the following preprocessing of data (proposed in (Menichelli, Hersleth, et al., 2014; Nguyen, Næs, Almøy, et al., 2018)) is applied to obtain uni-dimensional blocks of variables. PCA is first run on double-centered data, and the PCA scores on the first two components (T1, T2) were recorded. By doing so, instead of eight variables per each block, only two variables T1, T2 were used as inputs in PLS-PM. This strategy was used for all block of data (Nguyen, Næs, Almøy, et al., 2018).

As opposed to PLS-PM, the SO-PLS approach is based on estimating an independent model for each endogenous block, it can handle the multi-dimensionality in data blocks. Consequently, SO-PLS-PM does not require the splitting of a multi-dimensional block into several uni-dimensional blocks during the analyses (Menichelli, Almøy, et al., 2014; T. Næs et al., 2011). For SO-PLS-PM we compared solutions based on original data and two-dimensional blocks obtained by the same PCA procedure as used for PLS-PM. In both cases (original and PCA-obtained data), each data block was also double-centered, i.e. centering for each consumer and block before running SO-PLS-PM.

The R packages *plspm* (Sanchez, Trinchera, & Russolillo, 2017) and *semPLS* (Monecke & Leisch, 2012) are used for implementing PLS-PM. The computations of SO-PLS are done in Python while SO-PLS-PM in MATLAB with in-house codes.

4. Results

For both yoghurt and biscuit data sets, the path diagrams describe the relations between blocks of variables with respect to the sequence of cognitive and physiological processes when people consume a food product (Blundell et al., 2010). This diagram is depicted in Fig. 1a in which liking was incorporated before satiation and satiety, and then these three blocks together imparted portion (Nguyen, Næs, Almøy, et al., 2018). This diagram was used in the SO-PLS-PM analyses.

Contrary to SO-PLS-PM, PLS-PM requires the consideration of uni-dimensionality. For this purpose, PCA was applied on each block of data as preprocessing step, and the obtained uni-dimensional blocks were used instead of original blocks of data. Consequently, a new path diagram (Fig. 1b) is suggested for PLS-PM analyses. This is essentially the same diagram as in a), the only difference is that now each block is replaced by two different blocks with one interpretable variable (principal component) in each.

4.1. Yoghurt data

4.1.1. PLS-PM

Applying PCA on liking block (consumers in rows and ratings of products in columns), the results revealed how the first two components could be explained for liking, expected satiation, expected satiety and prospective portion size. Using sensory attributes as supplementary observations, the meanings of PCA components were investigated. Considering liking, for example, the first component was explained by viscosity with *Thick* and *Liquid* attributes located in the opposite sides, whereas the second component was characterized by the particle-size (*Sandy* and *Pieces*). These results were also observed for satiation and portion, however, for satiety, the components were switched in which the first component became particle-size and the second component was viscosity component. The loading plots were displayed in the supplementary material in Appendix A (Fig. A1). The two compnents explained around 50% of the variation and had a clear interpretation. Component 3 was also discussed briefly in (Nguyen, Næs, Almøy, et al., 2018), but this did contribute little to the interpretation and is therefore omitted here. These two components were used as separate blocks in the PLS-PM. This is beyond the scope of the present paper to discuss details of product characterizations, but they are available from (Nguyen, Næs, Almøy, et al., 2018). From now on, the paper will make focus on the first two components: the one related to viscosity (V) and the one related to particle-size (P), for example, Liking V will be the liking component driven by viscosity, Liking P will be the liking component driven by particle size, and so on.

Fig. 2 highlights the relations between the four data blocks using that notation (V, P) in which blue lines indicate positive relationships, red lines show negative relationships, dashed lines are no relation and the weights of the lines are the strengths of the relationships between two blocks. It is noted that all variables were standardized, in this way the path coefficients could be compared. The path coefficients are displayed with the corresponding P-values in parentheses. More specifically, liking has positive and strong effect on portion with path coefficients of 0.44 and 0.72 for the component V and P, respectively. Furthermore, liking is a good predictor for satiation and satiety. It is noteworthy that while liking directly influence satiation (*LikingV-SatiationV*: 0.30, *LikingP-SatiationP*: 0.37), it does not contribute directly to satiety for each component. On the other hand, satiation strongly (and directly) imparted satiety (*SatiationV-SatietyV*: 0.41, *SatiationP-SatietyP*: 0.48)

Until now, the relations between blocks have been considered according to each PCA component (V, P), the relations between blocks for the different principal components also provide noteworthy information. The direct, indirect, total effects and their P-values were found in Table 1. In this table, the relations with non-significances of any direct, indirect, total effects were eliminated. Among the significant relations, it is of interest to consider the relations between liking and satiety, especially, *SatietyV*. The direct relation *LikingP-SatietyV* was significant and negative (-0.29). In contrast, the relation *LikingV-SatietyV* was indirect and positive (0.15). With the negatively direct relation (-0.12), that resulted in no relation between *LikingV* and *SatietyV* in total effect.

In addition to the effects, for each regression in the structural model, R^2 (the proportion of variance in endogenous LV that is predictable from its independent LVs) was determined (Table 2). It was not surprising that *PortionP* was the most explained block with R^2 = 49.8%, followed by *SatietyV* (31.67%) and *SatietyP* (24.82%).

In summary, we can say that liking affected directly both portion, satiation and satiety. Neither satiation nor satiety affected portion in any significant way. Satiation had a direct effect on satiety. The direct effects dominated completely, none of the indirect effects were significant. The significant effects followed either P or V except the one direct effect from *LikingP* to *SatietyV*.

4.1.2. SO-PLS-PM

The essential step was to determine the number of components per each data block used in the SO-PLS-PM estimation. Based on the path diagram, three SO-PLS models were considered: (1) Liking → Satiation, (2) Liking + Satiation → Satiety, and (3) Liking + Satiation + Satiety → Portion. For each model, the number of components was selected from cross-validated prediction error, RMSEP (Måge, Mevik, & Næs, 2008).

The RMSEP plots, as function of the total number of components for all three regression methods, show that model 1 was optimized with 5 components of Liking; model 2 with 1 component of Liking and 5 components of Satiation; model 3 with 5 components of Liking, 0 component of Satiation and 0 component of Satiety (Fig. A2 in Appendix A).

Noted that the number of components was selected sequentially by optimizing for the first block and then for the next block while keeping the number of components of previous blocks fixed (sequential optimization). For model 2, the regression Liking → Satiety was first investigated, the RMSEP plot pointed out that this regression was optimized with 1 component of Liking (data not shown). For that reason, 1 component was used for the next step in which the regression Liking + Satiation → Satiety was considered. Consequently, the combination of 1 component of Liking and 5 components of Satiation was selected although those of 0 component of Liking and 5 components of Satiation was lower in RMSEP value (Fig. A2b). Actually, the difference between two combinations (1,5) and (0,5) was negligible.

Taking each SO-PLS model into account, the cumulative validated explained variances were displayed (Table 3). For model 1 (Liking → Satiation), with 5 components, Liking predicted 10.5% of variability of Satiation. For model 2 (Liking + Satiation → Satiety), Satiety was mostly explained by Satiation (15.2%, 5 components) when Liking (1 component) only explained 0.9% of Satiety variance. For model 3 (Liking + Satiation + Satiety → Portion), only Liking was considered as the regressor of Portion, it predicted 20.6% of Portion variance by using 5 components. These results indicate clearly a multi-dimensionality structure of each data block.

With optimized number of components, the direct, indirect and total effects were obtained. The SO-PLS-PM path diagram (Fig. 3) shows three main/significant relations based on the direct effects: *Liking-Portion*, *Liking-Satiation* and *Satiation-Satiety* with the path coefficients 20.64, 10.45 and 19.23, respectively. These results were in consistent with those of PLS-PM which emphasized the relation *Liking-Portion*, *Liking-Satiation-Satiety*. Basically, the relations *Liking-Portion* and Satiation-Satiety were two times higher than the relation *Liking-Satiation*. The relative strengths were a little bit different in PLS-PM results where the relations *Liking-Portion* and *Satiation-Satiety* were not twice as high as the relation *Liking-Satiation*, especially regarding to the component V. Apart from the relative strengths of relations, the only main difference is the lack of significant relation between Liking and Satiety. The indirect and total effects were displayed in Table 4. It is found that there were no indirect effects. Total effects were therefore the same to direct effects.

It was noted that the explained variances were used as the path coefficients; therefore, they were always positive. In order to point out the "signs" of these relations, PCP plots were obtained for each model. For model 1 (Liking → Satiation) and 3 (Liking + Satiation + Satiety → Portion), it was clear that Liking had a positive effect on Satiation and Portion due to the similar configurations between Liking, Satiation and Satiety (Fig. A3 in Appendix A). This results were in consistence with those of PLS-PM where Liking had an important role in predicting Satiation and Satiety. However, considering the relations in the model 2 (Liking + Satiation → Satiety), the loading plot of the explanatory blocks (i.e. Liking, Satiation) and response block (i.e. Satiety) shows that both Liking and Satiation positively imparted on Satiety. It was further explained when investigating the classification of these ratings on the PCP loading plots (Fig. 4). As can be seen from Y-loadings (Fig. 4b), the first component separated satiety ratings into two groups: one group (P7, P8, P4) was located on the left, and another group (P1, P3, P5, P6, P2) on the right side. This position was in line with the separations based on liking or satiation ratings (Fig. 4a). On the second component, the classifications of liking, satiation and satiety ratings were roughly consensus with P7, P1, P3 on the top and P4, P2, P5, P6 on the bottom of this component.

4.1.3. SO-PLS-PM on preprocessed data

To investigate the effect of the PCA preprocessing step on SO-PLS-PM results, the SO-PLS-PM is also applied on the two components data. Table 5 shows the direct effects (path coefficients) in this model are slightly different as compared with those of SO-PLS-PM on original data. The main relations were the same: *Liking-Portion* (31.8), *Liking-Satiation* (8.93), and *Satiation-Satiety* (20.18). Consequently, SO-PLS-PM could be used on original data without changing the main relations between variables.

4.2. Biscuit data

4.2.1. PLS-PM

The same strategy of analyses was applied to the biscuit data set. First, PCA was run on double-centered data; however, the PCA plots (Fig. B1 in Appendix B) did not show so clear and direct interpretation for the configurations of Liking, Satiation, Satiety and Portion as in the yoghurt data. It seemed to be similar classifications on the first component for Liking and Portion with the product s4w and s4wo on one side and the rest of products on the other side. However, on the second component, it was differently positioned: s3wo for Liking, and s3w for Portion on the positive side. The confused separations were also observed when considering satiation and satiety. For example, the product s1w was associated with the component 2 for Satiation, whereas it was related to the component 1 for Satiety. It implied that the meaning of the first two components was not really defined for different ratings (i.e. liking, satiation, satiety, portion). For that reason, we kept the names “1” and “2” as the first and second component in the next analyses. An alternative here could have been to let the different samples represent separate blocks of data as also discussed in (Menichelli, Hersleth, et al., 2014), but that would lead to an enormous number of blocks and relations that would be very difficult to interpret. We therefore kept the same procedure as for yogurt.

The PLS-PM path diagram (Fig. 5) shows the relations between data blocks with the corresponding path coefficients. The direct, indirect and total effects are shown in Table 6. In this sense, strong positive relations were mostly related to the component 1: *Liking1-Satiation1* (0.3), *Satiation1-Satiety1* (0.53), *Satiety1-Portion1* (0.48). There was only one significant relation with component 2: *Satiation2-Satiety2* (0.29). *Liking2* did not contribute significantly to the relations on the component 2. More specifically, the relations were not significant (*Liking2-Satiation2*, *Liking2-Satiety2*) or equal to 0 (*Liking2-Portion2*). In contrast, Liking1 was not only related to the component 1 but also to the component 2; for example, *Liking1-Satiation2* (0.2) in direct way and *Liking1-Satiety2* (0.19) in indirect way. In addition, *Satiation1* negatively imparted on *Portion2* with the path coefficient -0.27; that is, the relative rating of *Portion2* decreased 0.27 when *Satiation1* increased one unit.

Considering calibrated explained variances of data blocks in the structural model, the blocks related to the component 1 were explained more effectively than those linked to the component 2 (Table 7). Among the data blocks, the most explained block was *Portion1* (40.65%), and the less one was *Satiation2* (6.54%).

In summary, the paths related to the blocks marked by 1 were the dominating, this held for liking-satiation, satiation-satiety and satiety-portion. For the ones marked with 2, the dominating ones were satiation-satiety and maybe satiety-portion. Cross-over between 1 and 2 appeared almost from 1 to 2 (*Liking1-Satiation2*, *Liking1-Satiety2*, *Satiation1-Satiety2*), only one in the opposite direction (*Liking2-Satiety1*). As above, the direct effects were dominating, only indirect effects of *Liking1-Satiety1, Liking1-Satiety2* and *Satiation1-Portion1* were significant.

4.2.2. SO-PLS-PM

Like yoghurt data, three SO-PLS models were considered: (1) Liking → Satiation, (2) Liking + Satiation → Satiety, and (3) Liking + Satiation + Satiety → Portion. For model 1, the RMSEP plot showed that Satiation was not predicted by Liking (0 component of Liking). For model 2, 5 components of Satiation were selected for predicting Satiety. For model 3, Portion was explained by 2 components of Liking. These RMSEP plots were shown in Fig. B2 (Appendix B).

The validated explained variances were calculated for each SO-PLS model (Table 8). Model 1 had no predictive power and was not further explained. In model 2, 9.5% of variability of Satiety was explained by 5 components of Satiation and not by any components of Liking. Conversely, in model 3, only Liking predicted Portion; in particular, 2 components of Liking interpreted 7.1% of Portion variances.

With optimized components selected from each block, the relations between blocks were calculated (Table 9) and the path diagram was plotted (Fig. 6). No indirect effects were observed. According to Fig. 6, there were two main relations: *Satiation-Satiety* (15.04) and *Liking-Portion* (7.14). In this path model, the relation *Liking-Satiation* was not found to be significant, whereas it was in the PLS-PM estimation (*Liking1-Satiaion1*: 0.3 and *Liking1-Satiation2*: 0.2). Furthermore, the relation *Satiety-Portion* was not significant in SO-PLS-PM estimation, but considerable in the PLS-PM model (*Satiety1-Portion1*: 0.35). No indirect effects were found for SO-PLS-PM. In other words, the main difference in terms of significance are the paths between liking and satiation and satiety and portion. In fact, the relation Satiety-Portion appeared and was equal to 1.27, however, the bootstrap-based standard error was high (1.27). Consequently, this relation became non-significant.

PCP loading plots were used to explain the “signs” of the relations between blocks in the path model (Fig. 7). As can be seen from Fig. 7a, the relation *Satiation-Satiety* was positive because their configurations were consistent. In particular, the first component split the ratings (both satiation and satiety) into two groups: P2, P7, P8 on the negative side and P4, P5, P6 on the positive side. On the second component, while ratings of P3, P1 were positioned on the top, ratings of P5 on the bottom of the loading plot. The plot indicates the consensus classifications between satiation and satiety ratings, that is, when satiation ratings increased, satiety ratings also increased, and conversely. In other words, the relation satiation-satiety was considered as positive relationship. Likewise, *Liking-Portion* was considered as the positive relation (Fig. 7b).

4.2.3. SO-PLS-PM on preprocessed data

Again, SO-PLS-PM was applied to the preprocessed Biscuit data. Although the complexity of data increased, the effects (Table 10) were still similar as compared with those of SO-PLS-PM on the original data. Particularly, the main relations *Satiation-Satiety*, *Liking-Portion* were 14.53 and 7.27, whereas they were 15.04 and 7.14 in SO-PLS-PM on original data. It was noted that the relation Satiety-Portion was 5.58, but its standard error also high (4.81). Therefore, it was not significant. These results that SO-PLS-PM were also appropriate for complex data.

5. Discussion

The objectives of this paper were focused on the methodological comparison of PLS-PM and SO-PLS-PM, so the focus here is on the statistical implications rather than the perceptual interpretations of results. Special emphasis was given to a method proposed in (Menichelli, Hersleth, et al., 2014; Nguyen, Næs, Almøy, et al., 2018) for obtaining uni-dimensional blocks. More details on the sensory perception perspective can be read elsewhere in Nguyen el al. (2018) and Nguyen et al. (2019, in preparation).

Uni-dimensional blocks from complex data

To ensure the assumption of uni-dimensionality in PLS-PM, PCA was used as the preprocessing step for both two data sets. For yoghurt data, this strategy worked well when PCA loading plots of data blocks (i.e. liking, satiation, satiety, portion) were consistent, and then the meanings of components (i.e. viscosity, particle-size) were easily interpretable. This was in line with the SO-PLS-PM results in which the main relations were in agreement with those of PLS-PM. However, with an increase in the complexity of data in the biscuit sample, the PCA preprocessing encountered some problems regarding the numbers and meaning of the components. The PLS-PM explanations were also in line with the PCA components; however, in the biscuit data, it is not very clear due to the different classifications of consumer ratings (i.e. liking, satiation, satiety, portion) on PCA loading plots, leading to the difficulties in the PLS-

PM interpretations. For example, *Satiation1-Portion2* had the most strongly negative effect in the PLS-PM results, but it is hard to explain the underlying relation even when additional information is available (e.g., sensory attributes, instrumental parameters).

Splitting original blocks into uni-dimensional blocks can also make the path model more complicated if the original data are of certain complexity. More specifically, it enhances the amounts of data blocks in the path model, which in turn, create further relations from the interactions of new blocks. Of those, some relations seem to be confusing (e.g., *Liking2-Satiety1*, *Satiation1-Portion2*), resulting in the difficulty of interpretation of PLS-PM path model. In other words, the method of splitting based on PCA components was less successful for the biscuit data than for the yogurt data.

As opposed to PLS-PM, SO-PLS-PM is applied to original data without PCA preprocessing step, and then the interpretations are more straightforward. In addition, PCP loading plots are used to explain how different exploratory blocks related to response block. On the other hand, as can be seen from the PLS-PM path diagram, the relation *Liking-Satiety* is deemed significant for both Yoghurt and Biscuit data, but it is not in SO-PLS-PM. A possible explanation of this is that the resampling tests for the effects based on cross-validation are more conservative. Another possible and related explanation is that the standard PLS-PM is more prone to overfitting. To check this possible overfitting, the PLS regression of Satiety on Liking (data not shown) was employed, and the result pointed out that Liking explains very low variability of Satiety.

The direct, indirect and total effects

The effects are used to interpret the relations between variables in both PLS-PM and SO-PLS-PM; however, their definitions are different depending on the method used. In PLS-PM, direct effects (also called path coefficients) are the regression coefficients, whereas in SO-PLS-PM, they are the explained variances. That leads to differences in indirect and total effect calculations. For that reason, the comparison between PLS-PM and SO-PLS-PM on the path coefficients should focus on the main trends instead of the absolute values (see also (Romano et al., 2018)). As aforementioned, the values of path coefficients in SO-PLS-PM seemed to be lower than those of PLS-PM. That is reasonable because these values are “validated” explained variances calculated by cross-validation.

Research work is needed to further compare SO-PLS-PM to other path modelling methods such as Path-ComDim or RGSCA. In fact, each method can solve some issues of path modelling; therefore, the comprehensive comparisons help to guide researchers how to apply the most appropriate method regarding the specific dataset.

6. Conclusion

The main purpose of the path models here is to predict portion from other aspects as well as explain the roles of each consumer expectations. For Yoghurt data, although there are differences in the absolute values, two approaches (i.e. PLS-PM and SO-PLS-PM) show the same main tendencies: Liking is the essential regressor of Satiation and Portion; and Satiation mainly predicts Satiety. When the complexity of sensory properties increases, the uni-dimensionality is not handled easily by PCA preprocessing step (Biscuit data), the relation Liking-Satiation becomes complicated and difficult to interpret in the PLS-PM model. In other words, the splitting procedure tested is not always to be recommended in PLS-PM.

In this study, SO-PLS-PM reveals the ability to model data sets which violate the assumption of uni-dimensionality without requiring any data preprocessing step. With uni-dimensional data, SO-PLS-PM also works well. With SO-PLS-PM approach, one data block could consist of several variables which describe different aspects of this block. In this way, a general information or relationships are considered in the original framework. That makes the explanation more explicit and avoids the potential overfittings when applying standard PLS-PM on uni-dimensional blocks obtained by splitting original data blocks.

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Table 1. The PLS-PM direct, indirect and total effects (Yoghurt data).

Relations	Direct	Indirect	Total
LikingV → SatiationV	0.30 (0.001)	0.00 (1.000)	0.30 (0.001)
LikingV → SatietyP	0.00 (0.996)	0.11 (0.024)	0.11 (0.356)
LikingV → SatietyV	*-0.12 (0.272)*	*0.15 (0.010)*	*0.03 (0.798)*
LikingV → PortionV	0.44 (0.000)	0.03 (0.425)	0.47 (0.000)
LikingP → SatiationP	0.37 (0.001)	0.00 (1.000)	0.37 (0.001)
LikingP → SatietyP	0.13 (0.273)	0.15 (0.033)	0.28 (0.013)
LikingP → SatietyV	*-0.29 (0.001)*	*0.01 (0.939)*	*-0.28 (0.003)*
LikingP → PortionP	0.72 (0.000)	-0.03 (0.556)	0.69 (0.000)
SatiationV → SatietyP	0.18 (0.024)	0.00 (1.000)	0.18 (0.024)
SatiationV → SatietyV	0.41 (0.000)	0.00 (1.000)	0.41 (0.000)
SatiationV → PortionP	0.13 (0.104)	-0.01 (0.856)	0.12 (0.103)
SatiationP → SatietyP	0.48 (0.000)	0.00 (1.000)	0.48 (0.000)
SatiationP → SatietyV	0.17 (0.079)	0.00 (1.000)	0.17 (0.079)

V, P denote viscosity, particle-size component.

Direct effects were path coefficients; indirect effects were the product of responding direct effects, and total effects were sum of direct and indirect effects.

P-values of effects were stored in the parentheses.

Table 2. The PLS-PM explained variances (Expl. var) per each block (Yoghurt data).

Blocks	SatiationV	SatiationP	SatietyV	SatietyP	PortionV	PortionP
Expl. var (%)	11.22	15.41	31.67	24.82	22.37	49.80

Table 3. The SO-PLS-PM cumulative validated explained variances (Yoghurt data).

	Satiation	**Satiety**	**Portion**
Liking	10.5 (5)	0.9 (1)	20.6 (5)
Satiation		16.1 (5)	0 (0)
Satiety			0 (0)

Blocks in bold were the dependent blocks in the responsive SO-PLS models.

The number of components per each block were stored in the parentheses.

Table 4. The SO-PLS-PM direct, indirect and total effects (Yoghurt data).

Relations	Direct	Indirect	Total
Liking → Satiation	10.45 (2.68)	0 (0.88)	10.45 (2.39)
Liking → Satiety	0 (1.01)	0.86 (1.82)	0.86 (1.57)
Liking → Portion	20.64 (2.60)	0 (1.60)	20.64 (2.37)
Satiation → Satiety	19.23 (3.55)	0 (0.46)	19.23 (3.52)
Satiation → Portion	0 (1.27)	0 (1.27)	0 (0)
Satiety → Portion	0.03 (1.02)	0 (0.62)	0.03 (1.05)

Direct, indirect and total effects were defined in SO-PLS-PM point of view.

Direct effects were used as path coefficients in path diagram.

Standard errors of the effects were stored in the parentheses.

Table 5. The SO-PLS-PM direct, indirect and total effects (preprocessed Yoghurt data).

Relations	Direct	Indirect	Total
Liking → Satiation	8.93 (3.84)	0 (0)	8.93 (3.84)
Liking → Satiety	1.83 (1.71)	2.56 (2.83)	4.39 (3.86)
Liking → Portion	31.8 (5.03)	0 (0)	31.8 (5.03)
Satiation → Satiety	20.18 (4.61)	0 (0)	20.18 (4.61)
Satiation → Portion	1.01 (3.08)	1.42 (2.04)	2.44 (3.35)
Satiety → Portion	0 (1.91)	0 (1.91)	0 (0)

Direct, indirect and total effects were defined in SO-PLS-PM point of view.

Direct effects were used as path coefficients in path diagram.

Standard errors of the effects were stored in the parentheses.

Table 6. The PLS-PM direct, indirect and total effects (Biscuit data).

Relations	Direct	Indirect	Total
Liking1 → Satiation1	0.30 (0.032)	0.00 (1.000)	0.30 (0.032)
Liking1 → Satiation2	0.20 (0.060)	0.00 (1.000)	0.20 (0.060)
Liking1 → Satiety1	-0.03 (0.815)	0.19 (0.012)	0.16 (0.341)
Liking1 → Satiety2	0.18 (0.136)	0.11 (0.031)	0.29 (0.022)
Liking1 → Portion1	0.48 (0.000)	0.06 (0.426)	0.54 (0.000)
Liking1 → Portion2	0.09 (0.443)	-0.14 (0.112)	-0.05 (0.580)
Liking2 → Satiety1	-0.19 (0.066)	0.01 (0.882)	-0.18 (0.054)
Satiation1 → Satiety1	0.53 (0.000)	0.00 (1.000)	0.53 (0.000)
Satiation1 → Satiety2	0.18 (0.076)	0.00 (1.000)	0.18 (0.076)
Satiation1 → Portion1	-0.02 (0.837)	0.20 (0.051)	0.17 (0.174)
Satiation1 → Portion2	-0.27 (0.037)	-0.09 (0.334)	-0.36 (0.000)
Satiation2 → Satiety2	0.29 (0.090)	0.00 (1.000)	0.29 (0.090)
Satiety1 → Portion1	0.35 (0.022)	0.00 (1.000)	0.35 (0.022)
Satiety2 → Portion2	-0.19 (0.112)	0.00 (1.000)	-0.19 (0.112)

1, 2 denote the first and second component.

Direct effects were path coefficients; indirect effects were the product of responding direct effects, and total effects were sum of direct and indirect effects.

P-values of effects were stored in the parentheses.

Table 7. The PLS-PM explained variances (Expl. var) per each block (Biscuit data).

Blocks	Satiation1	Satiation2	Satiety1	Satiety2	Portion1	Portion2
Expl. var (%)	8.99	6.54	33.21	19.24	40.65	15.23

Table 8. The SO-PLS-PM cumulative validated explained variances (Biscuit data).

	Satiation	**Satiety**	**Portion**
Liking	0 (0)	0 (0)	7.1 (2)
Satiation		9.5 (5)	0 (0)
Satiety			0 (0)

Blocks in bold were the dependent blocks in the responsive SO-PLS models.
The number of components per each block were stored in the parentheses.

Table 9. The SO-PLS-PM direct, indirect and total effects (Biscuit data).

Relations	Direct	Indirect	Total
Liking → Satiation	0 (2.53)	0 (2.53)	0 (0)
Liking → Satiety	0 (2.22)	0 (2.22)	0 (0)
Liking → Portion	7.14 (3.08)	0 (2.95)	7.14 (1.09)
Satiation → Satiety	15.04 (2.98)	0 (0.84)	15.04 (2.87)
Satiation → Portion	0 (2.13)	0.63 (2.34)	0.63 (1.38)
Satiety → Portion	1.27 (1.27)	0 (1.80)	1.27 (1.53)

Direct, indirect and total effects were defined in SO-PLS-PM point of view.

Direct effects were used as path coefficients in path diagram.

Standard errors of the effects were stored in the parentheses.

Table 10. The SO-PLS-PM direct, indirect and total effects (preprocessed Biscuit data).

Relations	Direct	Indirect	Total
Liking → Satiation	1.53 (3.59)	0 (1.40)	1.53 (3.61)
Liking → Satiety	0 (2)	0 (2)	0 (0)
Liking → Portion	7.27 (4.44)	3.53 (2.74)	10.8 (5.26)
Satiation → Satiety	14.53 (4.37)	0 (1.37)	14.53 (4.26)
Satiation → Portion	0 (2.21)	5.53 (3.97)	5.53 (4.46)
Satiety → Portion	5.58 (4.81)	0 (0.72)	5.58 (4.84)

Direct, indirect and total effects were defined in SO-PLS-PM point of view.

Direct effects were used as path coefficients in path diagram.

Standard errors of the effects were stored in the parentheses.

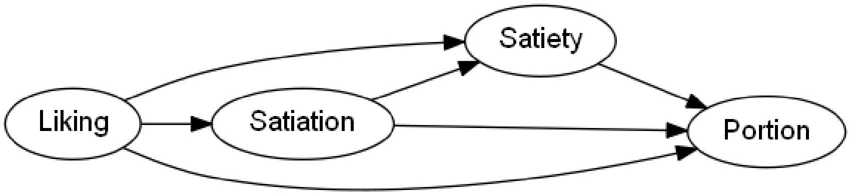


Figure 1a. Path diagram on the original data blocks.

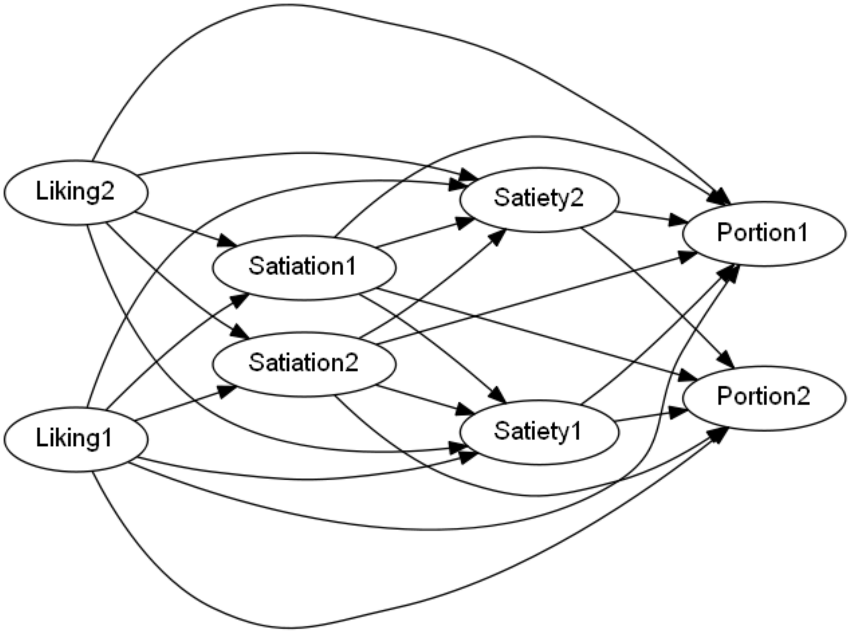


Figure 1b. Path diagram on split blocks based on PCA components.

Liking1 and Liking2 were liking for the first and second PCA components, respectively.

The other variables (Satiation1, Satiation2, Satitety1, Satiety2, Portion1, Portion2) were also defined in the similar way.

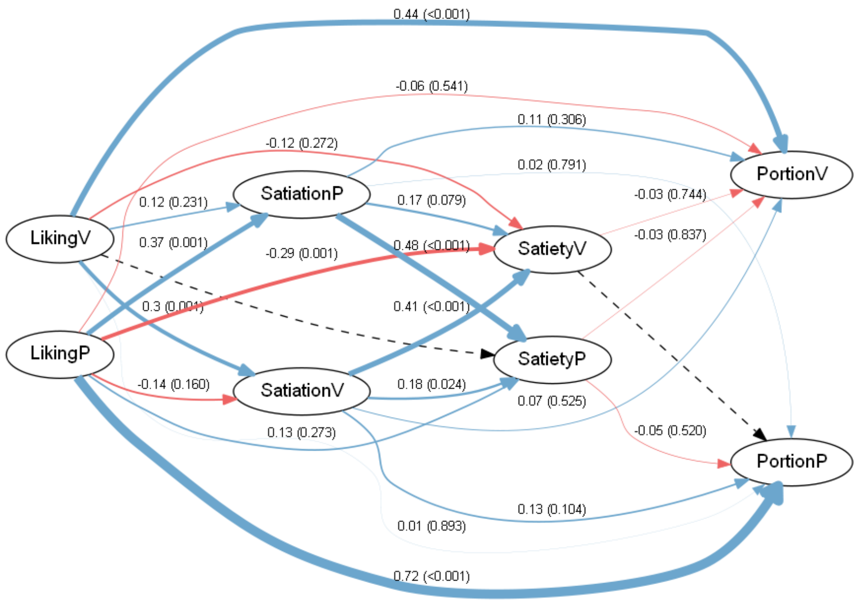


Figure 2. PLS-PM path diagram – Yoghurt data.

The 'blue' lines stood for the positive relations, the 'red' lines dedicated for negative relations and the numeric values together lines as the strengths of the relations between variables.

V and P were the notation of viscosity and particle-size dimension, respectively.

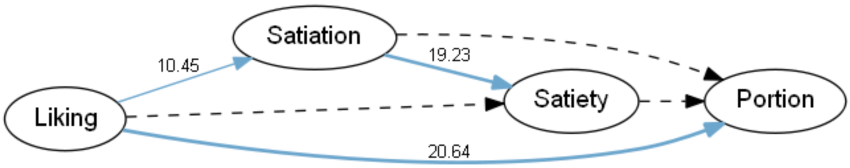


Figure 3. SO-PLS-PM path diagram – Yoghurt data.

The numeric values together with lines were path coefficients.

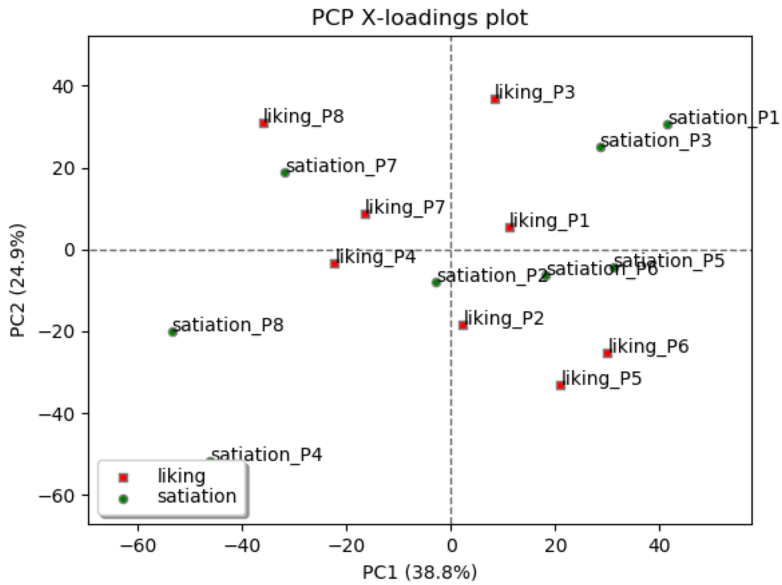


Figure 4a. PCP loading plots of exogenous blocks (Model 2) – Yoghurt data.

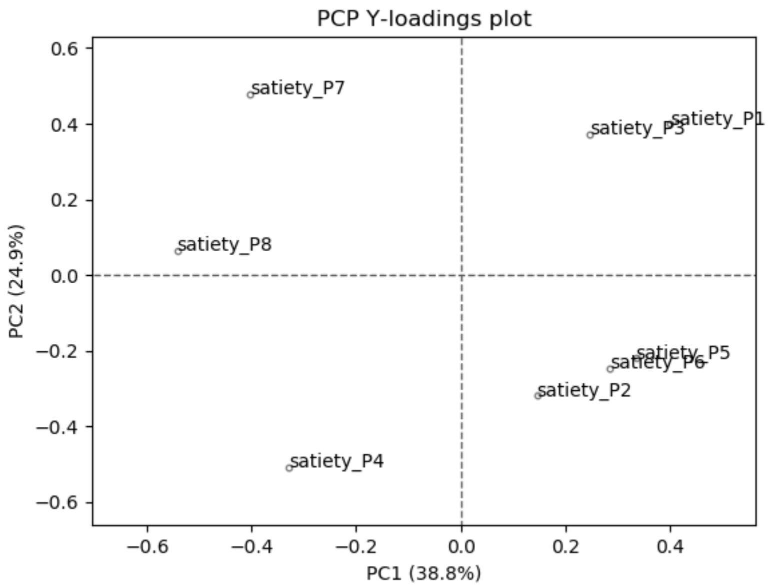


Figure 4b. PCP loading plots of endogenous block (Model 2) – Yoghurt data.

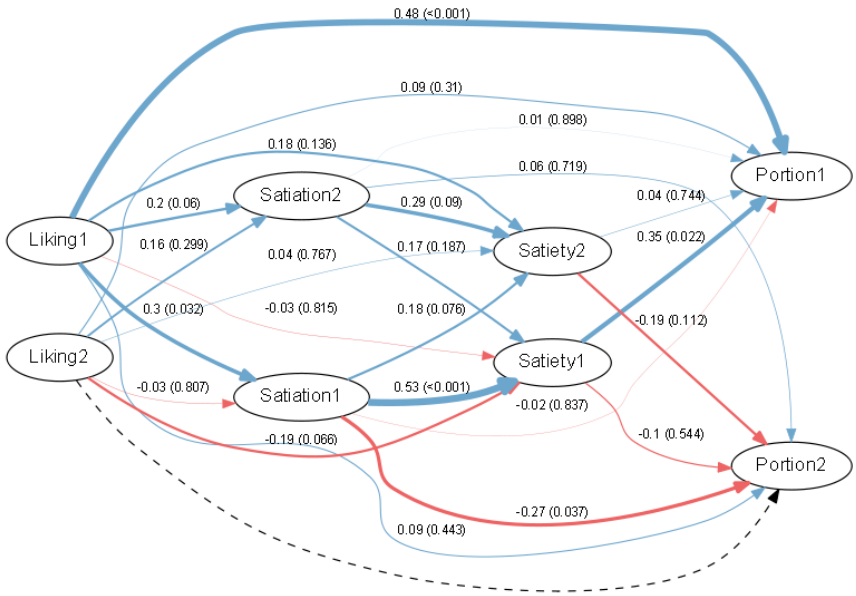


Figure 5. PLS-PM path diagram – Biscuit data.

1 and 2 were the notation of the first and second component.

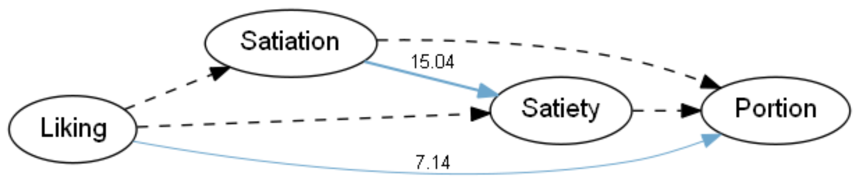


Figure 6. SO-PLS-PM path diagram – Biscuit data.

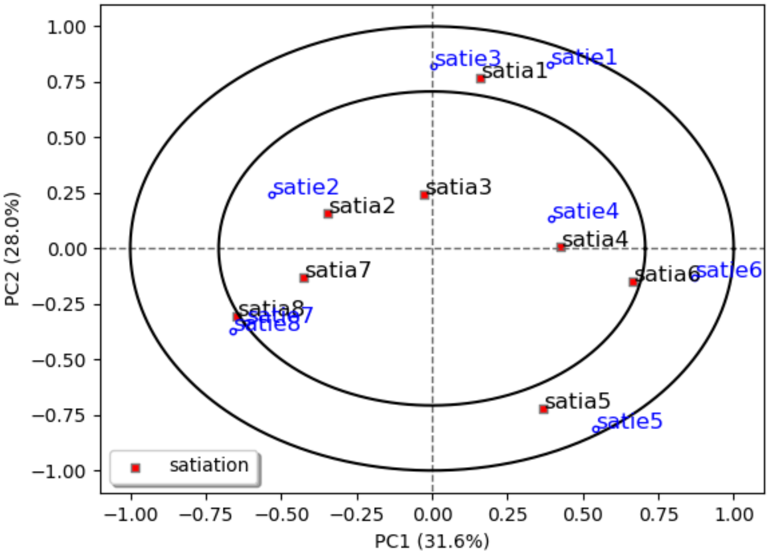


Figure 7a. PCP loading plots for Model II – Biscuit data.

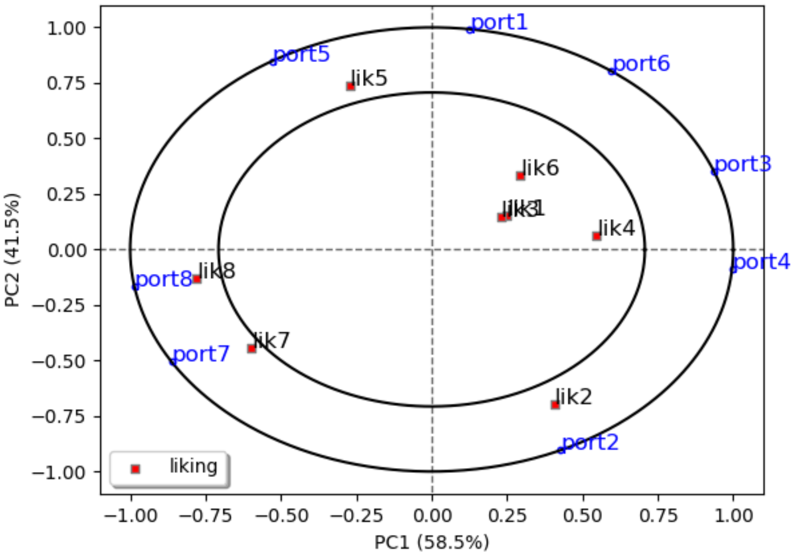


Figure 7b. PCP loading plots for Model III – Biscuit data.

Appendixes

Appendix 1 (Questionnaire in Paper 1)

Consumer test

Current hunger level: "How hunger do you feel right now?", rated on 100mm line scale, ranging from "Not hungry at all" to "Very hungry".

Acceptance: "How much do you like this bread?", rated on 9-point scale.

I don't like it at all				Neither like nor dislike				I like it very much
☐	☐	☐	☐	☐	☐	☐	☐	☐

Expected satiation: "How full do you think you would get eating this bread?", rated on 9-point scale.

Not full at all								Very full
☐	☐	☐	☐	☐	☐	☐	☐	☐

Expected satiety: "For how long do you think you would feel full from this bread?", rated on a 6-point scale.

Hungry again at once	Full for up to one hour	Full for up to two hours	Full for up to three hours	Full for up to four hours	Full for five hours or longer
☐	☐	☐	☐	☐	☐

CATA question for real samples

Please eat the rest of the bread sample, while you assess which attributes describe the bread.

☐ Good flavor	☐ Bad flavor	☐ Bitter flavor
☐ Grain/cereal flavor	☐ Sour flavor	☐ Taste of sourdough
☐ Yeast flavor	☐ Sweet flavor	☐ Not coarse
☐ Medium coarse	☐ Very coarse	☐ Airy
☐ Chewy	☐ Compact	☐ Crumbly
☐ Doughy	☐ Soft	☐ Hard
☐ Heavy	☐ Juicy	☐ Dry
☐ Porous	☐ Sticky	

☐ Appealing	☐ Fibour	☐ Health/nutritious
☐ Not appealing	☐ Satiating	☐ Suitable for breakfast
☐ Suitable for lunch	☐ Suitable for lunch pack	☐ Suitable for dinner
☐ Suitable for supper	☐ Unhealthy	☐ "Everyday" bread
☐ weekend bread	☐ Would buy	☐ Would not buy

CATA question for ideal sample

Check all attributes that describe your ideal bread.

☐ Good flavor	☐ Bad flavor	☐ Bitter flavor
☐ Grain/cereal flavor	☐ Sour flavor	☐ Taste of sourdough
☐ Yeast flavor	☐ Sweet flavor	☐ Not coarse
☐ Medium coarse	☐ Very coarse	☐ Airy
☐ Chewy	☐ Compact	☐ Crumbly

☐ Doughy ☐ Soft ☐ Hard

☐ Heavy ☐ Juicy ☐ Dry

☐ Porous ☐ Sticky

☐ Appealing ☐ Fibour ☐ Health/nutritious

☐ Not appealing ☐ Satiating ☐ Suitable for breakfast

☐ Suitable for lunch ☐ Suitable for lunch pack ☐ Suitable for dinner

☐ Suitable for supper ☐ Unhealthy ☐ "Everyday" bread

☐ weekend bread ☐ Would buy ☐ Would not buy

Statements regarding bread, health and satiety

How much do you agree/disagree with these statements?

When I buy/bake bread I think about satiating the bread is

Totally disagree				Neither agree nor disagree				Totally agree
☐	☐	☐	☐	☐	☐	☐	☐	☐

White bread is as healthy as coarse bread

Totally disagree				Neither agree nor disagree				Totally agree
☐	☐	☐	☐	☐	☐	☐	☐	☐

If I am going to get properly satiated, it is crucial that the bread is coarse

Totally disagree				Neither agree nor disagree				Totally agree
☐	☐	☐	☐	☐	☐	☐	☐	☐

When eating white bread, you need more slides to get satiated than if you eat coarse bread

Totally disagree				Neither agree nor disagree				Totally agree
☐	☐	☐	☐	☐	☐	☐	☐	☐

Demographics and habits regarding bread consumption

Gender

Age

Height

Weight

Education level (if consumers are students or employees)

How many days a week consumers ate break

To which meal consumers normally ate break (breakfast, lunch, dinner, supper, snack)

Appendix 2 (Questionnaire in Paper 3, 4)

A. Demography

1. What is your age?

2. What is your gender?

☐ Female

☐ Male

3. What is your height in centimeters?

4. What is your weight in kilograms?

B. Consumption and usage

1. How many days a week do you eat yoghurt?

☐ 7 days a week ☐ 5-6 days a week

☐ 3-4 days a week ☐ 1-2 days a week

☐ once a week or less ☐ never

2. Which meal do you usually eat yoghurt? (Multiple choice possible)

☐ Breakfast ☐ Lunch

☐ Dinner ☐ Supper

☐ Snack

C. Hunger and fullness question

Mental hunger factor

1. Rate the amount of food you currently desire [a]

2. Rate your current desire to eat your next meal [b]

3. Rate your current desire to eat something fatty

4. Rate your current desire to eat something salty

5. Rate your current desire to eat something savory

6. Rate your current desire to eat something sweet

7. Rate your current desire to eat your favorite food

8. Rate your current desire to eat a snack

9. Rate your current appetite

10. Rate your current feeling of fullness [b]

11. Rate your current feeling of hunger [b]

12. Rate your current motivation to eat

13. Rate the extent to which you are currently thinking of food [c]

14. Rate your current willingness to eat

15. Rate your desire for more of the food you last ate

16. Rate your current desire for a different food than you last ate [a]

Mental fullness factor

1. Rate your feeling of fullness from the food you last ate [b]

2. Rate your appetite satisfaction from the food you last ate

Physical hunger/fullness factor

1. Rate the extent to which you currently feel stomach pain [c]

2. Rate the extent to which you currently feel famished [c]

3. Rate the extent to which your stomach currently feels empty [c]

4. Rate the extent to which your stomach currently feels stuffed [c]

Most questions were present on general labeled magnitude scales. Exceptions are footnoted.

D. Attitudes toward healthfulness of foods on 7-point Likert scale

General health interest

1. The healthiness of food has little impact on my food choices.

2. I am very particular about the healthiness of food I eat.

3. I eat what I like and I do not worry much about the healthiness of food.

4. It is important for me that my diet is low in fat.

5. I always follow a healthy and balanced diet.

6. It is important for me that my daily diet contains a lot of vitamins and minerals.

7. The healthiness of snacks makes no difference to me.

8. I do not avoid foods, even if they may raise my cholesterol.

Light product interest

1. I do not think that light products are healthier than conventional products.

2. In my opinion, the use of light products does not improve one's health.

3. In my opinion, light products don't help to drop cholesterol levels.

4. I believe that eating light products keep one's cholesterol level under control.

5. I believe that eating light products keeps one's body in good shape.

6. In my opinion by eating light products one can eat more without getting too many calories.

Natural product interest

1. I try to eat foods that do not contain additives.

2. I do not care about additives in my daily diet.

3. I do not eat processed foods, because I do not know what they contain.

4. I would like to eat only organically grown vegetables.

5. In my opinion, artificially flavoured foods are not harmful for my health.

6. In my opinion, organically grown foods are no better for my health than those grown conventionally.

E. Attitudes toward taste on 7-point Likert scale

Craving for sweet foods

1. In my opinion it is strange that some people have cravings for chocolate.

2. In my opinion it is strange that some people have cravings for sweets.

3. In my opinion it is strange that some people have cravings for ice-cream.

4. I often have cravings for sweets.

5. I often have cravings for chocolate.

6. I often have cravings for ice-cream.

Using food as a reward

1. I reward myself by buying something really tasty.

2. I indulge myself by buying something really delicious.

3. When I am feeling down I want to treat myself with something really delicious.

4. I avoid rewarding myself with food.

5. In my opinion, comforting oneself by eating is self-deception.

6. I try to avoid eating delicious food when I am feeling down.

Pleasure

1. I do not believe that food should always be source of pleasure.

2. The appearance of food makes no difference to me.

3. When I eat, I concentrate on enjoying the taste of food.

4. It is important for me to eat delicious food on weekdays as well as weekends.

5. An essential part of my weekend is eating delicious food.

6. I finish my meal even when I do not like the taste of a food.

F. Consumer test

Acceptance rating: "How much do you like this yoghurt?", rated on LAM scale.

Expected satiation: "How full do you think you would get eating this yoghurt?", rated on SLIM scale.

Expected satiety: "For how long do you think you would feel full from this yoghurt?", rated on a 6-point scale from 1 = "hungry again at once" to 6 = "full for five hours or longer".

Hungry again at once	Full for up to one hour	Full for up to two hours	Full for up to three hours	Full for up to four hours	Full for five hours or longer
☐	☐	☐	☐	☐	☐

Ideal portion-size: "Imagine you are having this yoghurt for snack right now. How much of this yoghurt would you choose to consume?", rated by selecting how many times compared to <u>normal size</u> (commercial yoghurts).

One-third	A half	Two-third	One-time	One and a half	Two-times	Three-times
☐	☐	☐	☐	☐	☐	☐

CATA question: Choose all the attributes/ terms that apply to this yoghurt

Flavour/ taste

☐ Vanilla	☐ Oat flavour	☐ Cloying
☐ Sour	☐ Sweet	☐ Bitter

Texture

☐ Thick	☐ Gritty	☐ Sandy
☐ Dry	☐ Creamy	☐ Mouth-coating
☐ Chewy	☐ Sticky	☐ Dense
☐ Smooth	☐ Heterogeneous	☐ Homogenous
☐ Liquid		

Non-sensory

☐ Easy to swallow	☐ Difficult to swallow	☐ High calorie
☐ Low calorie	☐ Satiating	☐ Not very satiating
☐ Appealing	☐ Not appealing	☐ Suitable for breakfast
☐ Suitable for snack	☐ Suitable for supper	☐ Fibrous
☐ Healthy		

G. Mouth behavior

Please click the link below and describe how food is manipulated in your mouth

Link: http://www.surveygizmo.com/s3/3746759/academic

Appendix 3 (Questionnaire in Paper 4)

Acceptance rating: "How much do you like this biscuit?", rated on LAM scale.

Expected satiation: "How full do you think you would get eating this biscuit?", rated on SLIM scale.

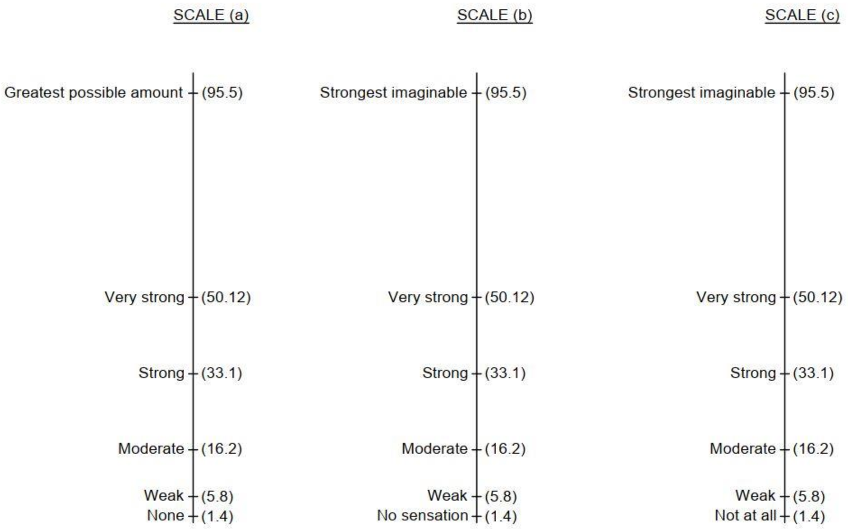
Expected satiety: "For how long do you think you would feel full from this biscuit?", rated on a 6-point scale from 1 = "hungry again at once" to 6 = "full for five hours or longer".

Hungry again at once	Full for up to one hour	Full for up to two hours	Full for up to three hours	Full for up to four hours	Full for five hours or longer
☐	☐	☐	☐	☐	☐

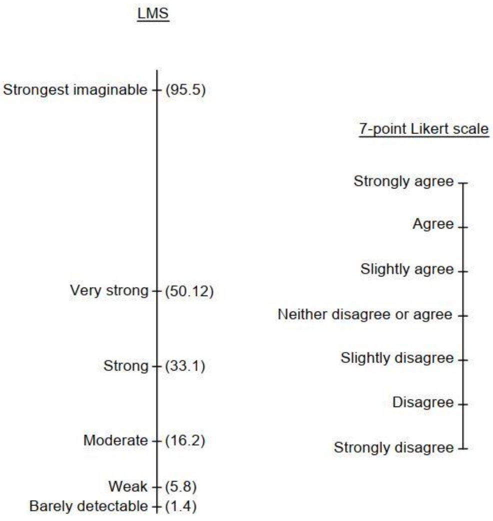
Ideal portion-size: "Imagine you are having this biscuit for snack right now. How much of this biscuit would you choose to consume?", rated by selecting how many times compared to normal size (commercial biscuit).

One biscuit	Two biscuits	Three biscuits	Four biscuits	Five biscuits	Six or more biscuits
☐	☐	☐	☐	☐	☐

Appendix 4 (Scales)



Modified LMS scales



LMS and 7-point scales

LAM and SLIM scales

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