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.

Keywords: *texture; viscosity; particle size; liking; satiation; satiety; portion size; PLS Path Modelling*

1. Introduction

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 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

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).

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).

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 et al. (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, Lahteenmaki, & Tuorila, 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 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.

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.

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 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.

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 (T. Næs, P. Brockhoff, & O. 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; T. Næs, P. B. Brockhoff, & O. Tomic, 2010).

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

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.

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.

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.

3.2. The prediction model

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*.

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 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.

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 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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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

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

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

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

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

Figure Captions

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

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.

Fig. 3. Path model of product related variables (*prod* model).

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

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

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).

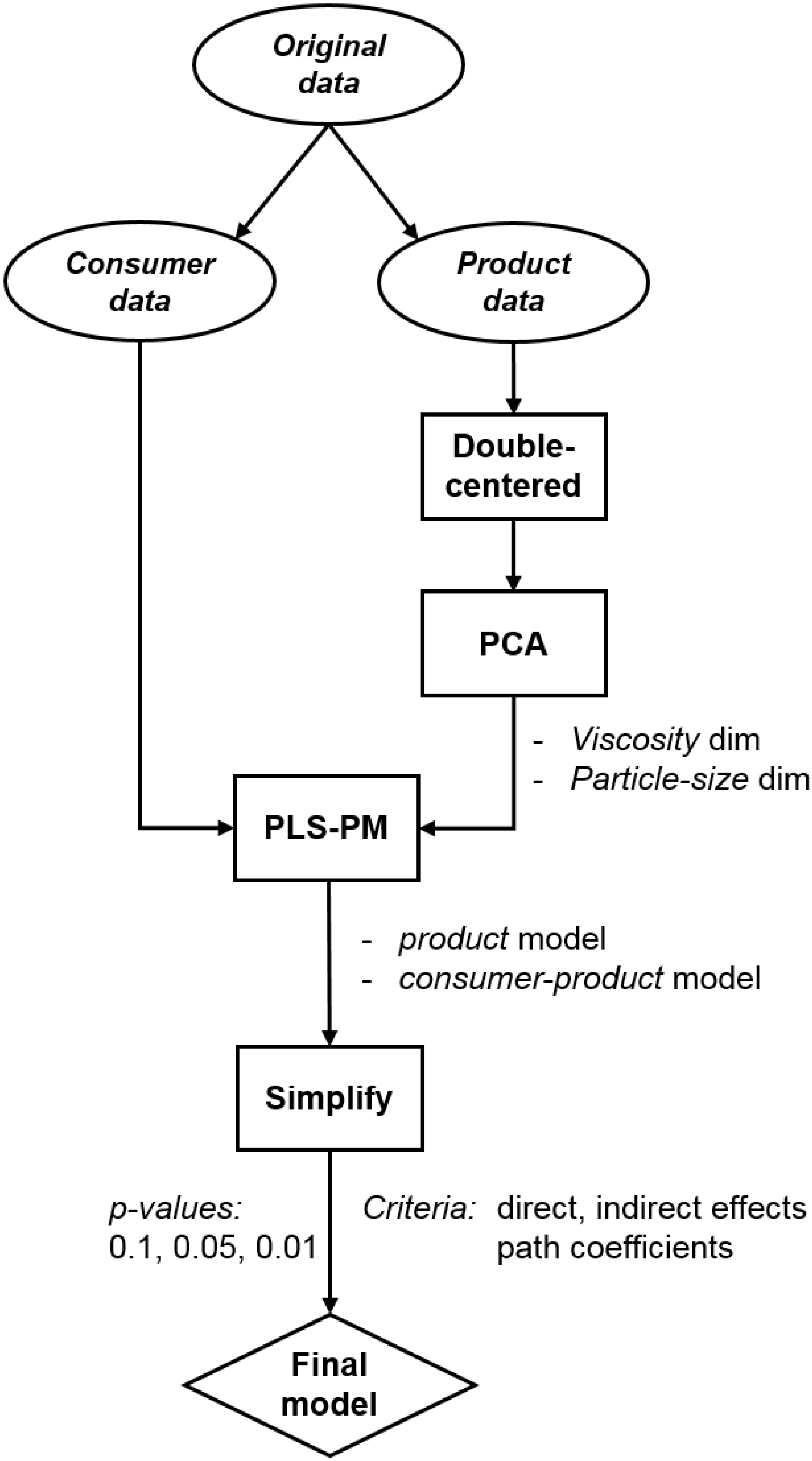
Fig. 7. Path diagram for the full *prod* model.

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.

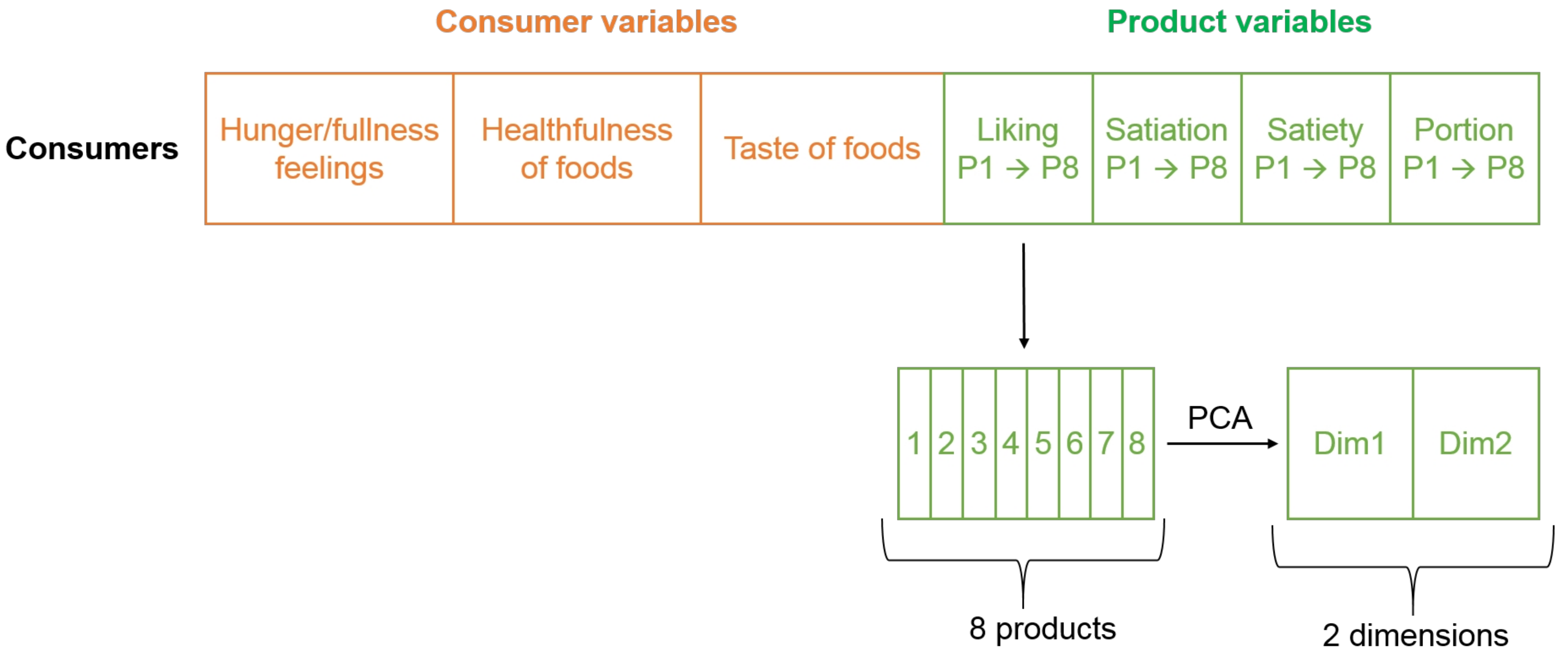
V and P were the notation of viscosity and particle-size dimension, respectively.

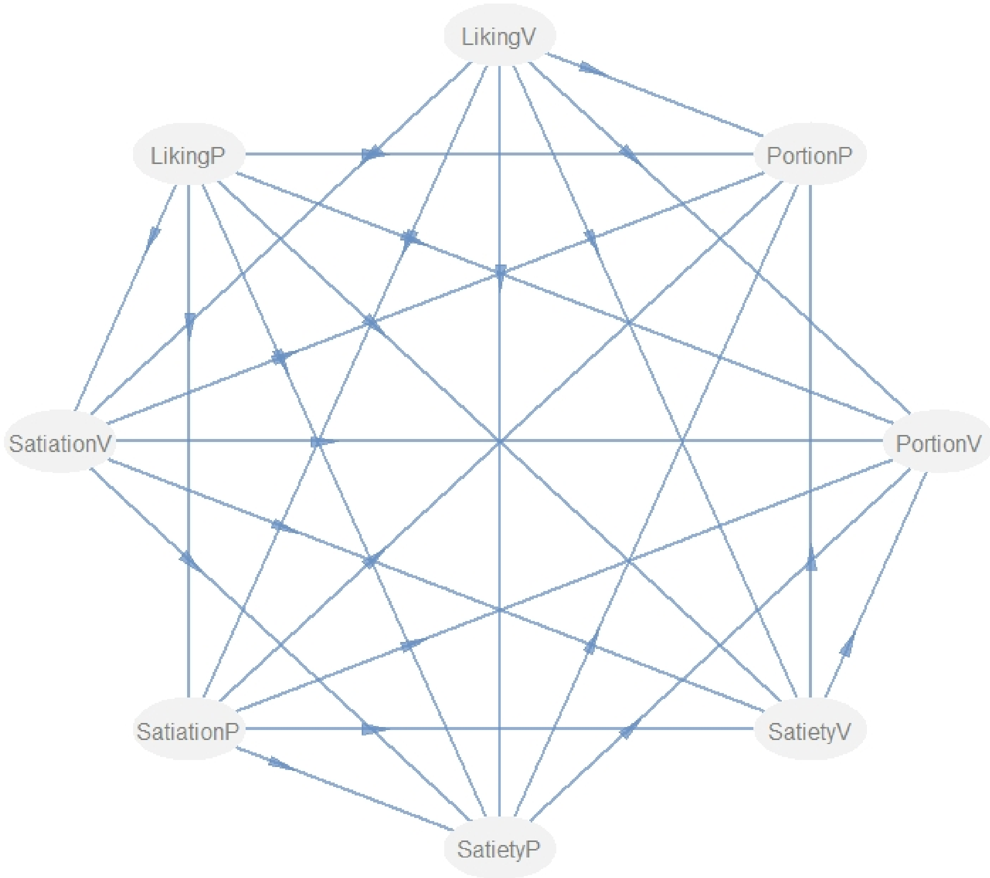
Fig. 8. Path diagram for the reduced *prod* model with p-values of 0.1.

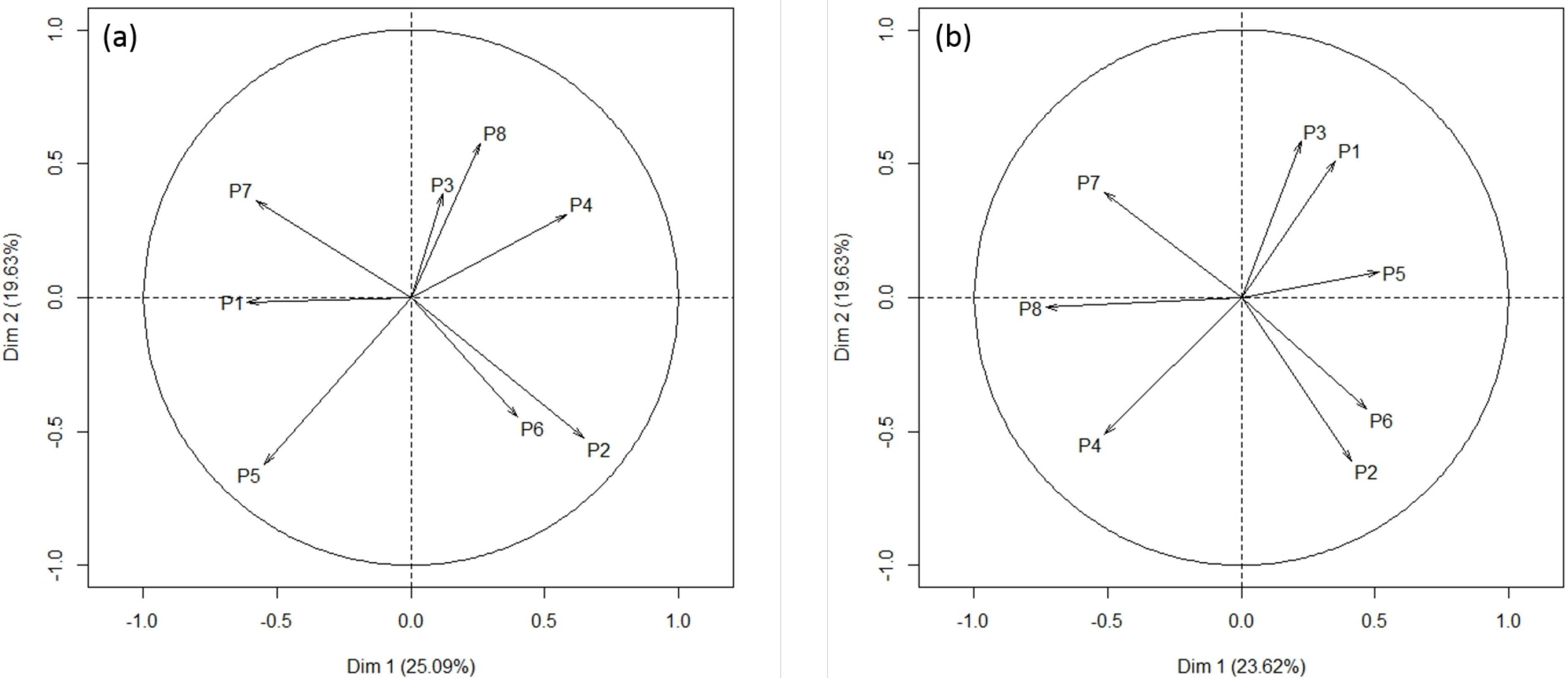
Fig. 9. The path diagram for consumer-product model with p-value of 0.05 for Chewers (a), *Crunchers* (b) and *Smooshers* (c).

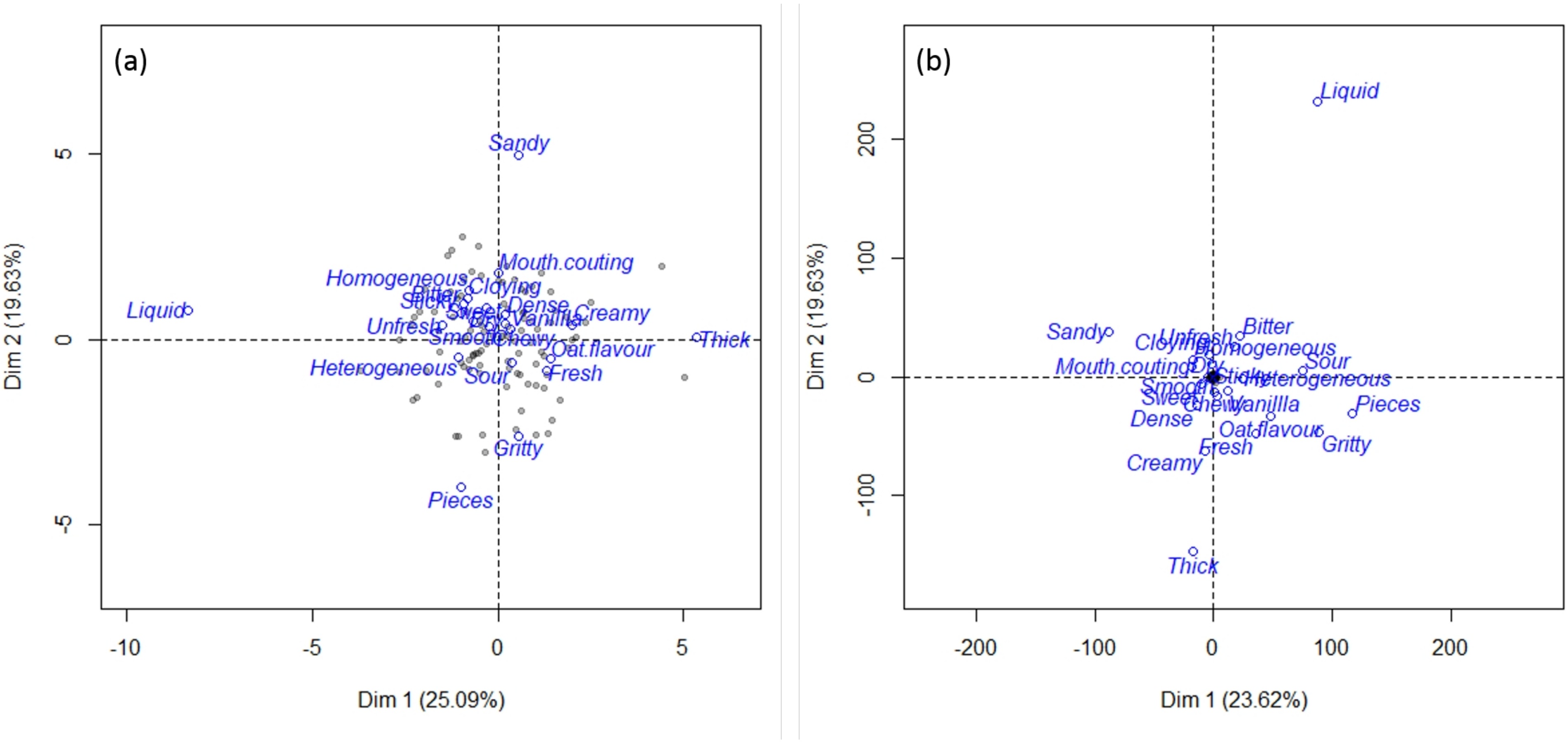


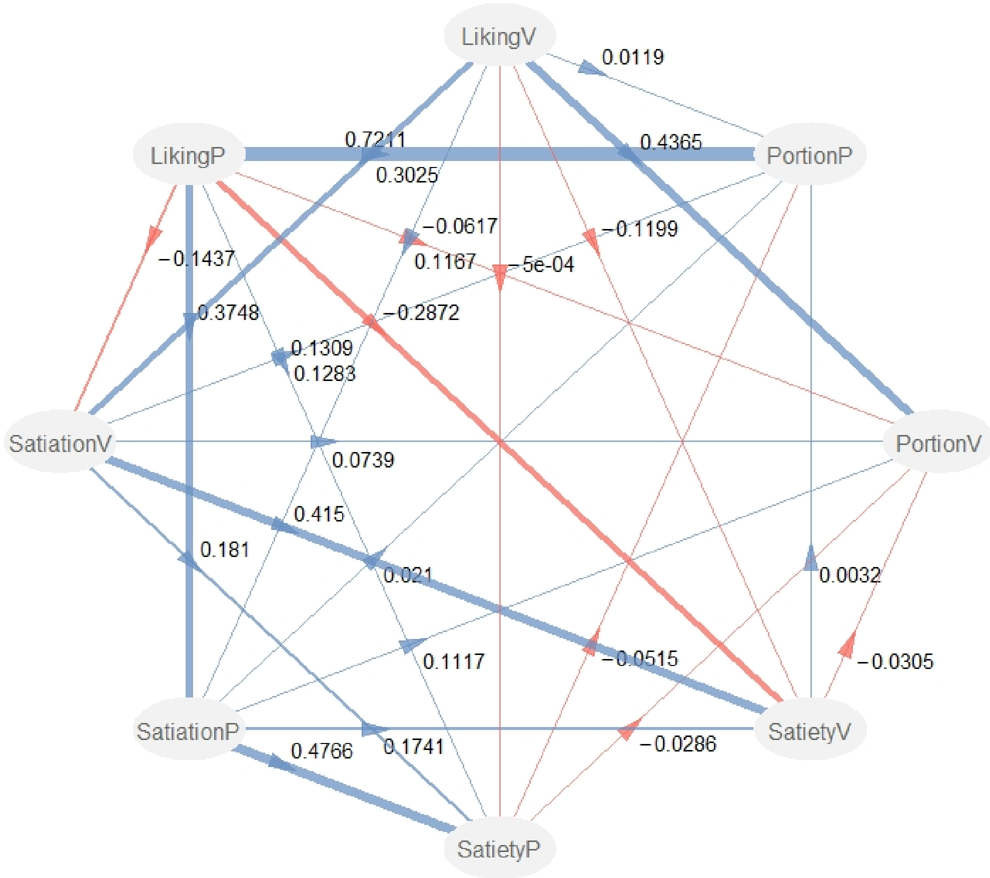
Original data
Consumer data
Product data
Double-centered
PCA
- Viscosity dim
- Particle-size dim
PLS-PM
- product model
- consumer-product model
Simplify
p-values:
0.1, 0.05, 0.01
Criteria: direct, indirect effects
path coefficients
Final model

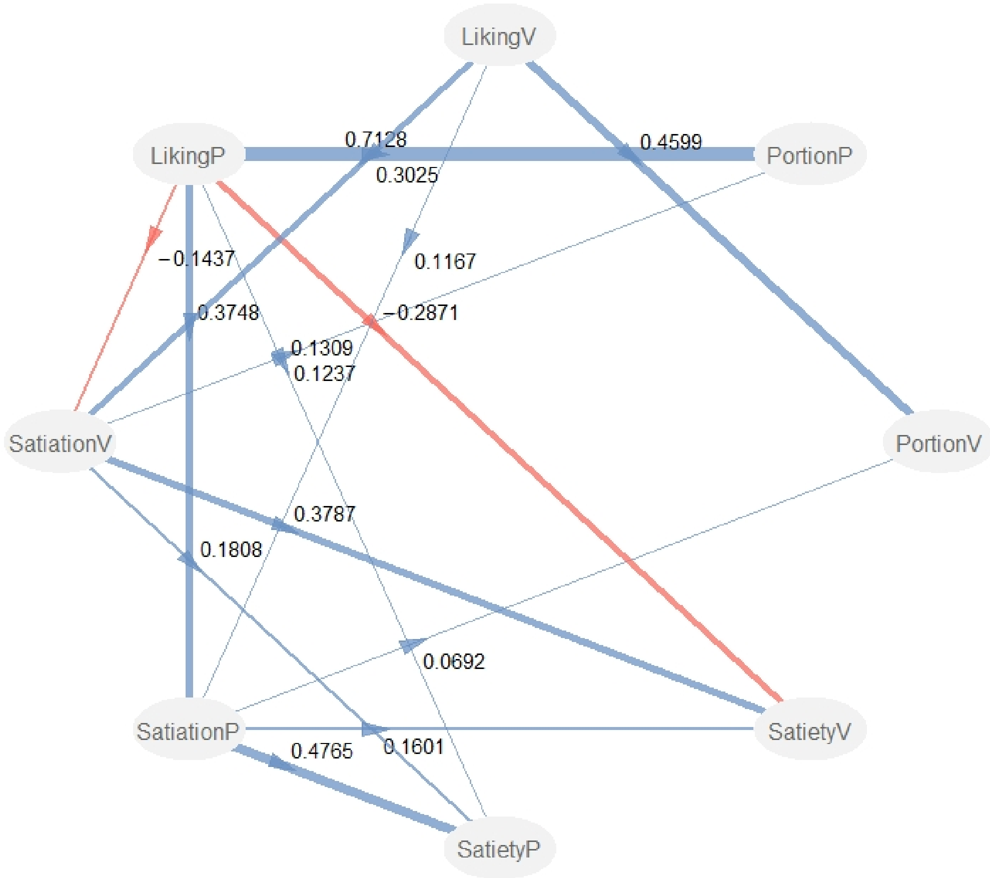

Consumer variables
Product variables
Consumers
Hunger/fullness feelings
Healthfulness of foods
Taste of foods
Liking P1 → P8
Satiation P1 → P8
Satiety P1 → P8
Portion P1 → P8
1 2 3 4 5 6 7 8
PCA
Dim1
Dim2
8 products
2 dimensions


LikingV
LikingP
PortionP
SatiationV
PortionV
SatiationP
SatietyV
SatietyP

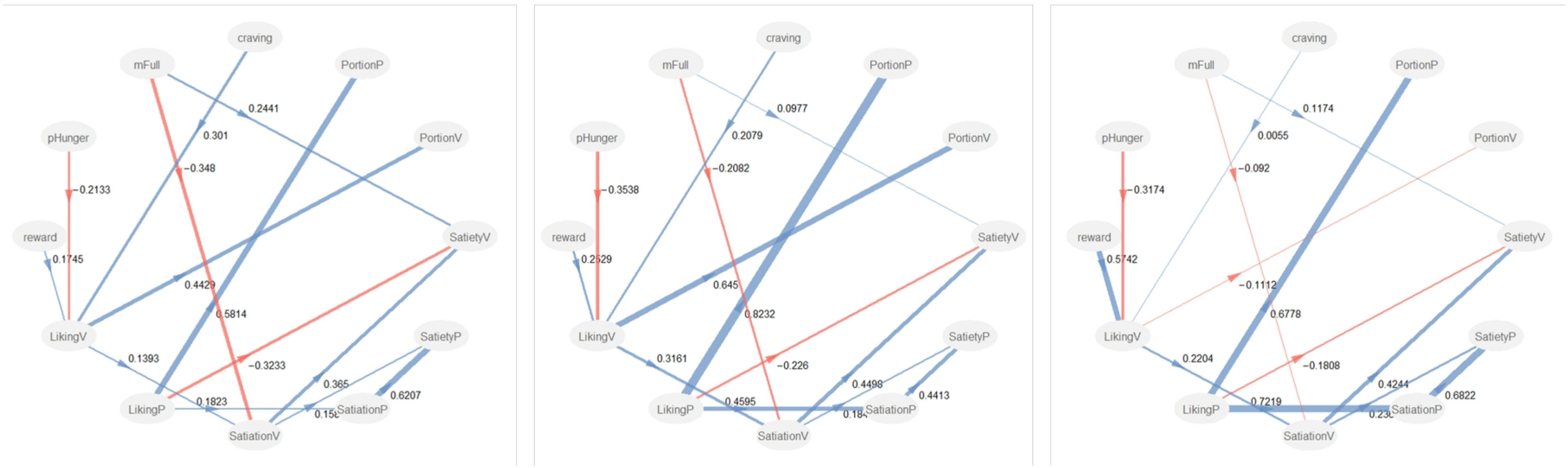

(a)
(b)
P1
P2
P3
P4
P5
P6
P7
P8
Dim 1 (25.09%)
Dim 2 (19.63%)
Dim 1 (23.62%)
Dim 2 (19.63%)
-1.0
-0.5
0.0
0.5
1.0


(a)
Sandy
Mouth.couting
Homogeneous
Cloying
Bitter
Sticky
Dense
Creamy
Liquid
Vanilla
Unfresh
Smooth
Chewy
Thick
Oat.flavour
Heterogeneous
Sour
Fresh
Gritty
Pieces
Dim 1 (25.09%)
Dim 2 (19.63%)
-10
-5
0
5
(b)
Liquid
Sandy
Bitter
Unfresh
Cloying
Homogeneous
Sour
Mouth.couting
Sticky
Heterogeneous
Smooth
Sweet
Chewy
Vanillla
Pieces
Dense
Oat.flavour
Gritty
Fresh
Creamy
Thick
Dim 1 (23.62%)
Dim 2 (19.63%)
-200
-100
0
100
200

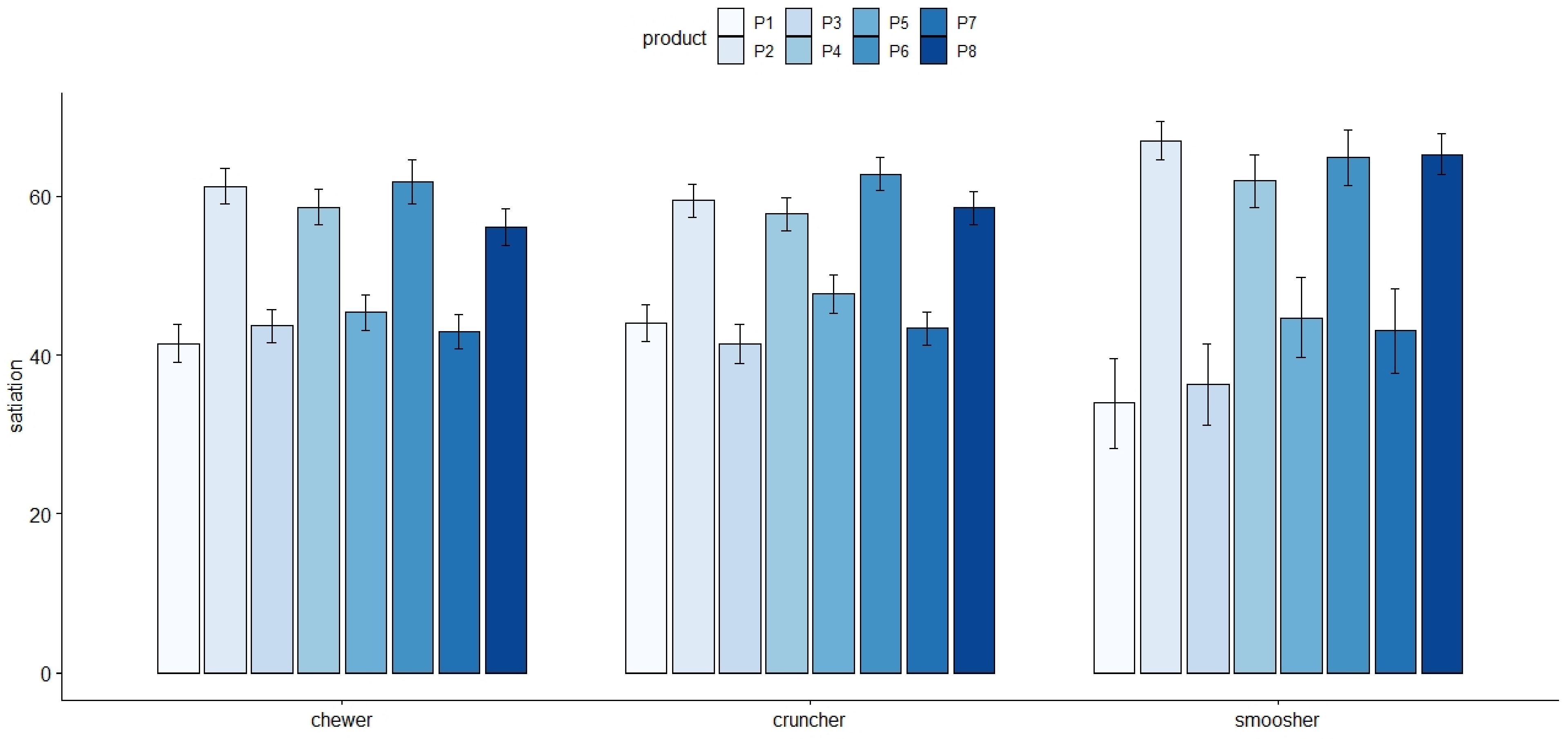

LikingV
0.0119
LikingP
0.7211
0.4365
PortionP
0.3025
−0.0617
−0.1199
0.1167
−5e-04
−0.1437
0.3748
−0.2872
0.1309
0.1283
SatiationV
PortionV
0.0739
0.415
0.181
0.021
0.0032
0.1117
−0.0515
−0.0305
SatiationP
SatietyV
0.4766
0.1741
−0.0286
SatietyP


LikingV
LikingP
PortionP
0.7128
0.4599
0.3025
−0.1437
0.1167
0.3748
−0.2871
0.1309
0.1237
SatiationV
PortionV
0.3787
0.1808
0.0692
SatiationP
SatietyV
0.4765
0.1601
SatietyP

(a) (b) (c)



craving
mFull
PortionP
0.2441
0.301
pHunger
PortionV
−0.348
−0.2133
reward
SatietyV
0.1745
0.4429
0.5814
LikingV
SatietyP
0.1393
−0.3233
0.365
0.6207
LikingP
0.1823
SatiationP
SatiationV
craving
mFull
PortionP
0.0977
0.2079
pHunger
PortionV
−0.2082
−0.3538
reward
SatietyV
0.645
0.8232
LikingV
SatietyP
0.3161
−0.226
0.4498
0.4413
LikingP
0.4595
SatiationP
SatiationV
craving
mFull
PortionP
0.1174
0.0055
pHunger
PortionV
−0.092
−0.3174
reward
SatietyV
0.5742
−0.1112
0.6778
LikingV
SatietyP
0.2204
−0.1808
0.4244
0.6822
LikingP
0.7219
SatiationP
SatiationV


product
P1
P2
P3
P4
P5
P6
P7
P8
satiation
60
40
20
0
chewer
cruncher
smoosher