Multi-block methods for investigating consumer acceptance of food

Multiblokkmetoder for analyse av
forbrukeraksept av mat

Metodi multi-blocco per analizzare
il gradimento dei consumatori di alimenti

Philosophiae Doctor (PhD) Thesis

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"Conducting data analysis is like drinking a fine wine. It is important to swirl and sniff the wine, to unpack the complex bouquet and to appreciate the experience. Gulping the wine doesn't work."

Daniel B. Wright

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CONTENTS

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PREFACE

The present doctoral thesis was financed by the Consumer-Check project, supported by the National Research Council of Norway and Norwegian food industry and by the Norwegian Institute of Food, Fishery and Acquaculture (Nofima).

The work was accomplished during the period from December 2009 to November 2013 under the main supervision of Prof. Tormod Næs (Nofima) and the co-supervision of Prof. Trygve Almøy (UMB), Ph.D. Nina Veflen Olsen (Nofima) and Prof. Solve Sæbo (UMB). The thesis is submitted to the Department of Chemistry, Biotechnology and Food Science of the Norwegian University of Life Sciences (UMB) for the degree of Philosophiae Doctor (Ph.D.).

The thesis consists of two parts: an introduction, structured in eight chapters, and five research papers. Chapter 1 gives a definition of multi-block methods in the sensometrics context and a brief explanation of typical data sets and relevant issues to be addresses. Chapter 2 presents aims and research approach. Chapter 3 is dedicated to the statistical methods adopted for achieving the scientific aims, followed by chapter 4 that links aims and methodologies. Chapter 5 summarises the enclosed papers and chapter 6 gives discussion about the novelty related to the methodological developments and results for each of the papers. Finally, chapters 7 and 8 offer some practical implications to the industry and conclude the first part of the thesis by proposing future perspectives.

ABSTRACT

Today's researchers easily gather large amounts of data of different origin and type. In sensory and consumer studies the objective is the collection of data to better understand consumer behavior in the market. Statistical methods are thus necessary to identify the relevant information and draw the best possible conclusions from such complex data sets.

In experimental sensory and consumer studies, information about different product attributes, many consumer characteristics and consumer acceptance or preference can be collected. Well-known statistical methods are used to reveal important information from multivariate data tables. These methods can, for example, identify key product attributes that determine which food people like. In many cases, anyway, one is also interested in more complex relations, such as the relations between different consumer characteristics and between consumer characteristics and acceptance. Another example is the relation between sensory and additional product attributes for the insight into drivers of liking. New method development is thus needed for combining or decomposing high order data tables in order to reveal the new types of underlying phenomena for the purpose of data analysis and prediction.

In this thesis a number of tools, so-called multi-block methods, are presented and discussed in order to handle multiple blocks of data arisen from experimental sensory and consumer studies. Some of the methods can be considered as extensions and some others as combinations of well-known statistical techniques. Their use is beneficial when analysing different types of data sets and when measurements can be organised in conceptually meaningful blocks. An example of such a natural division into blocks may be data of different properties considered on the same set of objects (e.g. sensory and chemical attributes of products; consumer habits and attitudes). Multi-block strategies are here developed with the aim of improving knowledge on the consumer acceptance of food products, by means of different types of product attributes and/or consumer characteristics. When product, consumer and acceptance data are included in one single study, the different dimensionality between blocks will be the main issue. In addition, a deep understanding of consumer acceptance requires insight into average acceptance patterns and individual differences. Consumer heterogeneity and strategies for segmenting the population of consumers are thus investigated throughout the thesis. The multi-block methods proposed in the present thesis are clear, easy to reproduce in standard software packages and flexible in their use. Results show the potential of these methods for the understanding of consumers in general and for improved insight into consumer individual differences. This is important for products development, successful marketing strategies and other practical implications for the industry.

SAMMENDRAG

Dagens forskere samler lett inn store mengder data av ulike typer. I sensorikk- og forbrukerstudier er målsettingen med datainnsamlingen å få bedre forståelse av forbrukerens oppførsel i markedet. Statistiske metoder er nødvendige for å avdekke relevant informasjon og trekke best mulige konklusjoner fra slike komplekse datasett.

I sensorikk- og forbrukerstudier kan for eksempel informasjon om ulike produktegenskaper, forbrukerkarakteristikker og forbrukeraksept eller preferanse, samles inn. Det finnes etablerte statistiske metoder for å avdekke viktig informasjon i multivariate datasett. Disse metodene kan for eksempel identifisere viktige produktegenskaper som avgjør hvilken mat folk liker. I mange tilfeller er man i tillegg interessert i mer komplekse sammenhenger, for eksempel mellom ulike forbrukerkarakteristikker og mellom forbrukerkarakteristikker og aksept for et produkt. Et annet eksempel er sammenhengen mellom sensorikk og produktegenskaper for å få innsikt i hva som gjør at man liker produktet. Utvikling av nye metoder er derfor nødvendig for å kombinere og bryte ned komplekse data, for å avdekke nye typer underliggende fenomener.

I denne avhandlingen blir en rekke statistiske verktøy, såkalte multiblokkmetoder, presentert, og anvendelser på data fra sensorikk- og forbrukerstudier blir diskutert. Metodene er utvidelser og kombinasjoner av velkjente statistiske teknikker. Multiblokkmetodene er nyttige når man skal analysere data som kan ordnes i begrepsmessig meningsfulle blokker. Et eksempel der man kan ordne dataene i slike naturlige blokker er der ulike egenskaper blir vurdert på samme objekt (for eksempel sensoriske og kjemiske egenskaper hos produkter, og holdninger og vaner hos forbruker). Multiblokkstrategiene er her utviklet med mål om å få økt kunnskap om forbrukeres aksept av matvarer, ved hjelp av ulike typer produktegenskaper og/eller forbrukerkarakteristikker. Når data om produkt, forbruker og aksept er inkludert i en enkelt studie, blir ulik dimensjon mellom blokkene hovedutfordringen. En dyp forståelse av forbrukeraksept krever i tillegg innsikt i både gjennomsnittlige akseptmønstre og individuelle forskjeller. Uensartethet mellom forbrukerne og strategier for segmentering av forbrukerpopulasjonen er derfor et gjennomgående tema i avhandlingen. Multiblokkmetodene som blir lagt frem i denne avhandlingen er tydelige, fleksible, og lar seg utføre med standard softwarepakker. Resultater viser potensialet til disse metodene for å forstå forbrukere generelt, og få bedre innsikt i individuelle forskjeller mellom forbrukere. Dette er viktig for å utvikle produkter, skape vellykkede markedsstrategier, og andre praktiske implikasjoner for industrien.

COMPENDIO

Attualmente l'attività di ricerca non riscontra particolari difficoltà nel reperire ingenti quantità di dati e flussi informativi. Negli studi sperimentali di analisi sensoriale e dei consumatori vengono lavorati grandi database con l'obiettivo di migliorare la conoscenza relativamente ai comportamenti di mercato dei consumatori. Si rendono quindi necessari metodi statistici appropriati che consentano di gestire una tale moltitudine di informazioni e contemporaneamente estrarre informazioni rilevanti per giungere a conclusioni concrete.

Nel contesto attuale vengono raccolte informazioni riguardanti diversi attributi dei prodotti, varie caratteristiche dei consumatori e il gradimento o le preferenze che gli stessi evidenziano. Alcuni noti metodi statistici sono stati concepiti proprio per evidenziare informazioni rilevanti da tabelle di dati multivariati, per identificare, ad esempio, gli attributi di prodotto che rivestono un ruolo significativo nel gradimento di alimenti da parte dei consumatori. In molti casi, comunque, si è interessati a relazioni più complesse, come le relazioni tra le diverse caratteristiche dei consumatori e tra queste caratteristiche ed il gradimento dei consumatori. Un ulteriore esempio è dato dalla relazione esistente tra gli attributi sensoriali e le proprietà supplementari dei prodotti, con l'obiettivo di cogliere quale di questi aspetti guidi il gradimento finale dell'alimento. L'implementazione di nuovi metodi statistici risulta necessaria per combinare o disaggregare le informazioni contenute in complessi database, al fine di far risaltare i meccanismi di gradimento sottostanti utili a stabilire successivamente attività di marketing mirate in un' ottica previsionale.

La tesi presenta diversi strumenti denominati multi-block methods sviluppati appositamente per l'analisi e la gestione di blocchi multipli di dati provenienti da studi sperimentali di analisi sensoriale e dei consumatori. Alcuni dei metodi possono essere considerati un'estensione ed altri una combinazione di ben note tecniche statistiche. Il loro utilizzo è importante quando si analizzano diversi tipi di dati e quando le misurazioni possono essere organizzate in blocchi significativi dal punto di vista concettuale. Un esempio di tale divisione naturale in blocchi può riguardare dati di varie proprietà considerate sullo stesso insieme di oggetti (gli attributi sensoriali e chimici dei prodotti, le abitudini e gli atteggiamenti dei consumatori). Strategie multi-blocco vengono qui sviluppate con l'obiettivo di migliorare la conoscenza del gradimento dei consumatori di prodotti alimentari, tramite l'informazione riguardante attributi di prodotto e/o caratteristiche dei consumatori. Nei casi in cui i dati rguardanti prodotti, consumatori e gradimento vengano analizzati in un unico ambito, la differente dimensionalità di questi blocchi di dati costituisce il problema principale da affrontare. Inoltre, per una profonda comprensione del gradimento dei consumatori, si richiede un'analisi approfondita sia a livello di popolazione che a livello di singoli individui. L'eterogeneità dei consumatori e le

strategie per la segmentazione della popolazione di consumatori sono quindi oggetto di studio in tutta la tesi. I metodi multi-blocco proposti nella presente tesi sono chiari, facili da riprodurre in pacchetti software standard e flessibili nel loro utilizzo. I risultati mostrano le potenzialità di questi metodi per la comprensione dei consumatori in generale, per una migliore conoscenza delle differenze individuali dei consumatori ed anche per lo sviluppo dei prodotti, strategie di marketing di successo e altre implicazioni pratiche per l'industria.

ABBREVIATIONS AND ACRONYMS

ANOVA	ANalysis Of VAriance
ANCOVA	ANalysis of COVAriance
CA	Conjoint Analysis
PREFMAP	External preference mapping
MDPREF	Internal preference mapping
PCA	Principal Component Analysis
GPA	Generalised Procrustes Analysis
MLR	Multiple Linear Regression
PCR	Principal Component Regression
PLSR	Partial Least Squares Regression
PLS-2	Partial Least Squares Regression with more than one response variable
PLS-DA	Partial Least Squares Discriminant Analysis
FCM	Fuzzy C-means clustering
PLS-PM	Partial Least Squares Path Modelling
MV	Manifest Variable
LV	Latent Variable
SO-PLS	Sequential Orthogonalised Partial Least Squares
PCP	Principal Components of Prediction

LIST OF PUBLICATIONS

This thesis is based on the following papers:

1. Endrizzi, I., Menichelli, E., Johansen, S. B., Olsen, N. V., & Næs, T. (2011). Handling of individual differences in rating-based conjoint analysis. *Food Quality and Preference*, 22(3), 241-254.

2. Menichelli, E., Olsen, N. V., Meyer, C., Næs, T. (2012). Combining extrinsic and intrinsic information in consumer acceptance studies. *Food Quality and Preference*, 23(2), 148-159.

3. Menichelli, E., Kraggerud, H., Olsen, N. V., Næs, T. (2013) Analysing relations between specific and total liking scores. *Food Quality and Preference*, 28, 429-440.

4. Menichelli, E., Hersleth, M., Almøy, T., & Næs, T. (2014). Alternative methods for combining information about products, consumers and consumers' acceptance based on path modelling. *Food Quality and Preference,* 31, 142–155.

5. Menichelli, E., Almøy, T., Tomic, O., Olsen, N. V., & Næs, T. (under revision). The SO-PLS approach to Path Modelling in consumer science. *Food Quality and Preference.*

PART I

INTRODUCTION

1. BACKGROUND

Experimental sensory and consumer studies (Grether & Wilde, 1984; Lawless & Heymann, 2010; Næs, Brockhoff, & Tomic, 2010) play an important role in food science and industry for the understanding of food properties and human acceptance, preference and buying behaviour. Sensory profiling studies use a trained panel for describing products as objectively as possible according to a set of sensory attributes. In consumer studies the products are tested by a preferably representative group of consumers, in order to investigate what people like or prefer. Consumers may also be asked to fill in questionnaires about demographics, attitudes and habits for the understanding of consumer heterogeneity and thus for segmentation.

In order to enhance marketing strategies and product development, industries also look for insight into the relations between the different types of data arisen from the mentioned studies, i.e. between the data sets of product properties, characteristics of the individuals and consumers' market behaviour. The development of statistical methods able to uncover valuable information from these large and complex data sets is thus strongly needed.

1.1 Multi-block in sensometrics

In the field of sensory and consumer science the new method developments are primarily organised in the discipline called sensometrics. In sensometrics, as in other disciplines with statistical orientation, a main problem is to analyse measured or calculated variables for a set of observations collected in a data table. This data set, defined as a collection of related variables, is called a block. The predictor or independent block can for instance contain properties for a set of food products. Several techniques can then be used for analysing the data, in order to identify the underlying phenomenon that causes most of the variability. The predictor block may also be related to a response (dependent), which in this context is represented by the consumers' acceptance or preference for products.

Several types of data sets, both predictor and dependent, may be collected to investigate a specific problem. The statistical techniques that can be used for the analysis on several data-blocks simultaneously are called multi-block methods (Höskuldsson, 2008; Kohonen, Reinikainen, Aaljoki, Perkiö, Väänänen, & Höskuldsson, 2008; H. Martens, Anderssen, Flatberg, Gidskehaug, Høy, Westad, et al., 2005; Næs, Tomic, Afseth, Segtnan, & Måge, 2013; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005; Westerhuis, Kourti, & MacGregor, 1998). The basic requirement is that these blocks have one mode or dimension in common (Smilde, Westerhuis, & Boque, 2000; van den

Berg, Povlsen, Thybo, & Bro). In experimental sensory and consumer studies it is possible to collect information about (i) product attributes of a different nature, (ii) many consumer characteristics and (iii) various acceptance variables. In the case (i) the common dimension is given by the products themselves, i.e. a series of measurements and experiments is performed on a set of products. For the product attributes, problems arise for instance when the variables are both categorical and continuous, or when result can be hard to interpret owing to the large number of variables. In the case (ii) the consumers constitute the common mode and the consumer characteristics are usually treated in a parallel way for explaining the acceptance, even when they may be of different nature and may thus also influence each other. Finally (iii), more than one response information can be collected. In this case different approaches can be followed according to the common mode chosen (products or consumers) to investigate the relations between different highly collinear acceptance values. All the mentioned types of data blocks can also be included in a single study, in order to detect the influence of product attributes and consumer characteristics on acceptance. The different dimensionality between the blocks will in this case be the main issue.

1.2 Typical data sets

Product attributes

For an optimised product formulation, products are involved in objective assessments that analytically evaluate the sensations triggered by the intrinsic product properties. This is the core of sensory evaluation, consisting of the use of human senses for evaluating the sensory attributes of a product (Amerine, Pangborn, & Roessler, 1965). It is a scientific method comprising different techniques for accurately measuring the human responses to food in such a way that the potentially biasing effect coming from additional external information about the product (e.g. brand, origin, price) is minimised (Lawless & Heymann, 2010). Other intrinsic attributes, like chemical properties or spectroscopic information, can also be considered. The focus on intrinsic product attributes is however not sufficient to meet the requirements of today's fast moving markets, since consumers are also influenced by other product information such as brand, price or labelling (Olsen, Menichelli, Meyer, & Næs, 2011). Both intrinsic and extrinsic attributes are taken into account in this thesis.

Affective evaluation: preference and acceptance

Affective evaluation relates to product assessments collected from untrained subjects that are preferably representative of the target population of consumers for the specific product. The consumer tests can be performed according to preference or acceptance. This thesis focuses on the latter, i.e. on the rating of consumer liking (or alternatively probability of buying, probability of choice, etc.) without requiring a comparison between the products (Lawless & Heymann, 2010). Usually a seven- or nine- point hedonic scale is used for rating the consumer responses to the products, ranging for instance from "Dislike extremely" to "Like extremely" (Peryam & Girardot, 1952). Commonly, the acceptance evaluation aims at expressing total liking, i.e. the overall impression of a product. Sometimes, as in this thesis, different liking evaluations related to different sensory modalities (Bi & Chung, 2011; Moskowitz & Krieger, 1995) or to different contexts and situations (Blake, 2008; Guinard, Uotani, & Schlich, 2001) are also considered.

Consumer characteristics

In today's business world, companies recognise that they cannot appeal to all consumers in the market by using a mass marketing strategy. Each consumer comes from a different background, lives in different area and has different interests. The collection of information about socio-demographics, attitudes, lifestyle orientations or purchase habits is thus extremely useful to understand consumer heterogeneity in market behaviour (Balan, Chua, Choong, Chang, & Say, 2013; Kubberød, Ueland, Rødbotten, Westad, & Risvik, 2002; Nu, MacLeod, & Barthelemy, 1996; Næs, Lengard, Johansen, & Hersleth, 2010; Verbeke, 2005). By identifying how different consumers behave it is possible to determine their needs and to translate this information into marketing strategies (Gray, Armstrong, & Farley, 2003; Nunes & Cespedes, 2003). This is usually done by defining consumer groups according to specific consumer characteristics. Socio-demographics are here involved because in many studies proved to be market-relevant attributes (see e.g. Balan, Chua, Choong, Chang, & Say, 2013; Libertino, Ferraris, Osornio, & Hough, 2012; Nu, MacLeod, & Barthelemy, 1996; Olsen, Menichelli, Sørheim, & Næs, 2012). In this work attitudinal measures and habits in food consumption are also included, since informative of consumer needs and thus able to define groups that are efficiently predictive of purchase behaviour (Hollywood, Armstrong, & Durkin, 2007).

1.3 The dimensionality issue

In a product investigation, each of the J products has been measured by K attributes, reflecting sensory descriptors, design variables, chemical measurements and so on. The resulting data set from intrinsic attributes is given by a three-way data structure, a special case of multi-block data, in which a set of two-way matrices have both the same objects and the same variables. In this context the structure is: products by attributes, for each of the assessors. In practice one often averages across subjects, since the main reason for having several assessors in a panel is that more precise assessments of product attributes are obtained. In this thesis both the extrinsic and intrinsic attributes are then organised according a two-way structure. These data are collected in a data table of dimensions JxK.

The data obtained from affective evaluations are also organised in a two-way structure: J products have been assessed by L consumers, usually with respect to overall liking, with results collected in the acceptance data table of dimension JxL. As already mentioned, consumers can in principle evaluate different types of liking, resulting in Q tables of acceptance data. For the case of different liking variables, the structure will then be three-way. The latter will also be taken into account in this thesis.

Furthermore, each of the L consumers have been typified by M characteristics, comprising demographic variables like gender, age, income, education, etc., as well as attitudes to food and consumption habits. The resulting data set is modelled according to a two-way data structure and will be a main focus throughout the entire thesis, since bearer of individual differences information. The third data table has dimensions LxM.

Since the available data sets have different dimensions (Fig.1), they need to be shaped and treated in such a way that it is possible to extract and visualise structures in the acceptance data, in light of additional information about products and consumers. Statistical methods are thus necessary to handle data sets of different dimensionality and to explore their relations. In the present thesis attention is given to consumer data – acceptance data relations (paper I), product data – acceptance data relations (papers II-III) and product data – consumer data – acceptance data relations (papers IV-V).

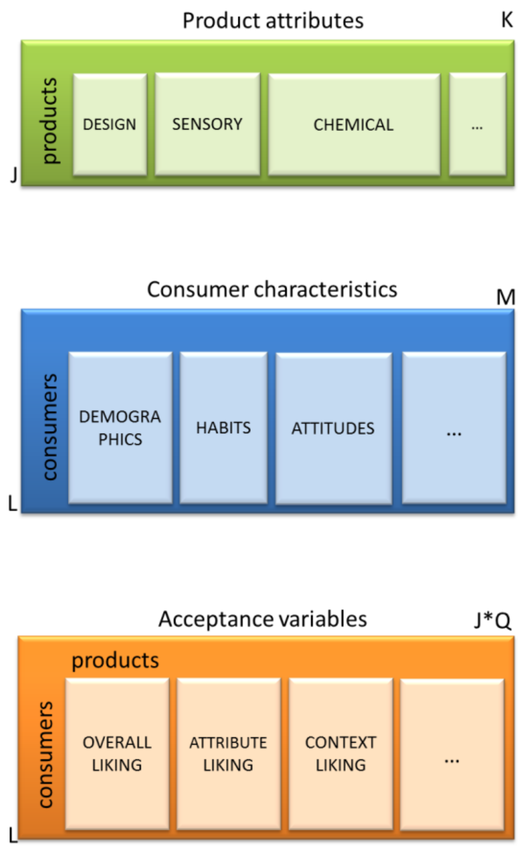

Figure 1. The available data sets with different dimensionality.

1.4 Average effects and individual differences

In experimental consumer studies it is important to understand not only the general population liking patterns but also the consumer acceptance at individual level. The investigation of consumer heterogeneity is crucial for generating knowledge about consumers. In particular, in case of consumer groups with opposite liking opinions, mean consumer effects only indicate general trends that do not reveal actual preferences. Often individual differences are analysed in terms of so-called segmentations, i.e. one looks primarily at differences between groups of consumers which are found similar in some way (Johansen, Hersleth, & Næs, 2010; Næs, Kubberød, & Sivertsen, 2001; Vigneau & Qannari, 2002; Wedel & Kamamura, 1998; Westad, Hersleth, & Lea, 2004).

There are two conceptually different ways of analysing individual differences and perform a segmentation. One of them is to analyse the liking pattern first and then relate the obtained results to external consumer characteristics. If segmentation is applied, this is often referred to as *a posteriori* segmentation. Another possible approach is to analyse groups of consumers directly defined by the consumer characteristics. This is called *a priori* segmentation. The analyses of individual differences need to be flexible in their applicability to studies with different types of data available.

2. AIMS AND RESEARCH APPROACH

2.1 Aims

The overall objective of the present thesis is the development of statistical methods for the insight into the relations between several data sets, i.e. so-called multi-block methodologies, in the context of sensory and consumer science. In particular, the thesis aims at answering the following questions:

1) How to study average effects and individual differences in the same modelling framework? (paper I)
2) How to define which intrinsic product attributes are driving the liking and how to combine them with the extrinsic additional product information? (papers II-III)
3) How to combine and analyse both product and consumer data for understanding the acceptance pattern? (papers IV-V)

In this thesis special attention will be devoted to investigating consumer heterogeneity. For a deep understanding of consumer acceptance, the study of individual differences can be done by means of either *a priori* or *a posteriori* segmentation strategies.

Consumer heterogeneity may also be profiled by means of relations with product attributes and consumer characteristics. In particular paper I, and in general all the papers included in this thesis, dedicate part of the focus on how to obtain insight into individual differences from different perspectives.

2.2 Multi-block framework

For the aim of this thesis, the data sets mentioned in sections 1.2 and 1.3 can be shaped in the so-called L-shape data structure (Fig.2). The main issue is to extract and visualise structures in the acceptance data cube Y in light of additional information both about the rows in Y, given in the product matrix X, and about the columns in Y, given in the consumer matrix Z (H. Martens, et al., 2005).

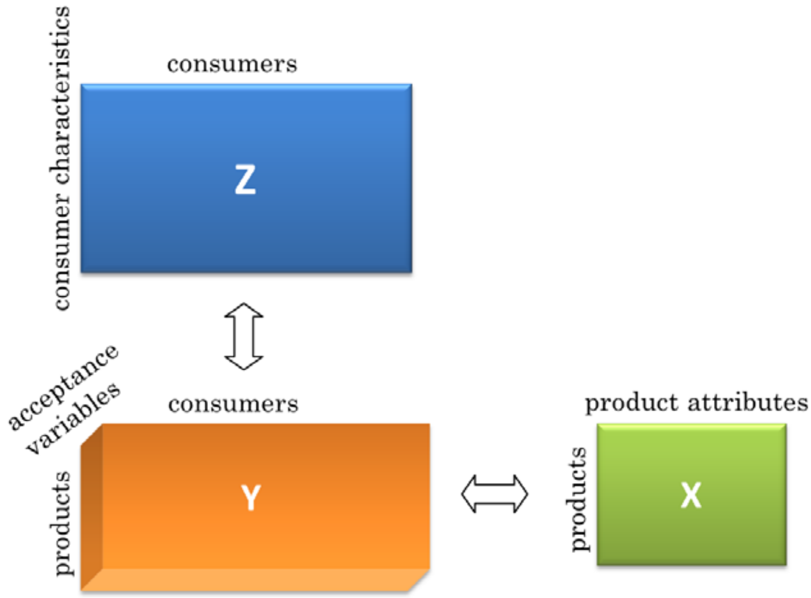

Figure 2. The L-shape data structure for the multi-block framework in sensory and consumer studies.

These matrices can be further divided according to the variables' nature (see e.g. Figure 1). This entails to consider a multi-block data structure, where both the predictor matrices X and Z and the dependent Y are divided into several sub-blocks. As indicated above, the consumer characteristics can sometimes be split in a natural way into blocks of data with a structure among them. How to decompose the data will depend on the specific situation, the problem to be addressed and the collected information available.

2.3 Research strategy

Through various studies the thesis answers the questions addressed in section 2.1 by means of investigation of the data sets relations at three different levels (Figure 3):

1) consumer data – acceptance data level (paper I)

The understanding of both general tendencies in the population and heterogeneity between consumers is important. Identifying different acceptance patterns in relation to consumer characteristics related to demographics, attitudes or habits, is important for improved understanding of consumers in general, for product development and for development of good marketing strategies.

2) product data – acceptance data level (papers II-III)

Very often intrinsic and extrinsic product attributes are investigated in independent tests, but this may often be insufficient. Sensory analysis needs to be combined with modern market research methods in order to develop integrated approaches that are able to evaluate both types of attributes and possible interactions between them.

Another important aim is to provide information about the most important aspects of liking. This means that results should give insight not only in relation to the actual products used in the experiment, but they should also identify the drivers of liking and thus possible alternative combinations of attributes with a potential for an even higher liking.

3) product data – consumer data – acceptance data level (papers IV-V)

This allows understanding of which attributes are important for the acceptance of which consumers. One may also be interested in a deeper insight in how different consumer characteristics relate to each other. For this purpose a major problem is to combine blocks of data with different dimensionality. The methodologies should be general enough to be applied to conjoint studies (Section 3.1), preference mapping (Section 3.4) and also their combination.

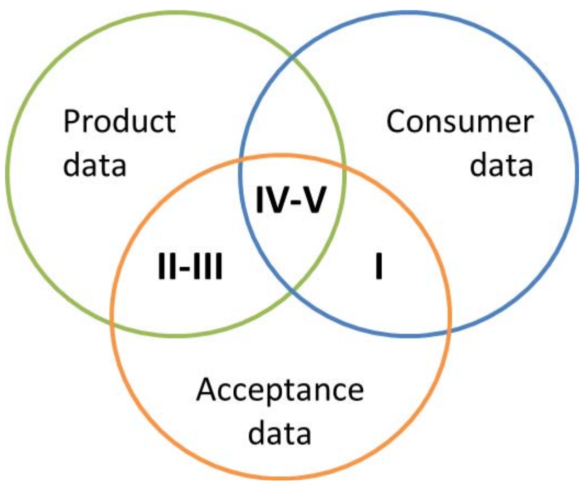

Figure 3. A visual representation of the research strategy adopted in the present thesis.

3. STATISTICAL METHODS

In the following, each of the statistical methods considered in the present thesis is briefly presented and related to the included papers (see also Table 1).

	Paper I	Paper II	Paper III	Paper IV	Paper V
Mixed models	Conjoint analysis with main, interaction and consumer effects. ANOVA residuals model.	Main effects and interactions for extrinsic, intrinsic and consumer factors. Significance tested in each group.		Main product and consumer effects.	Main product and consumer effects.
PCA	Study on the ANOVA residuals matrix.	Sensory profiling. Detection of subsets of products to be combined with extrinsic attributes.	Sensory profiling. Differences between liking modalities.	Liking pattern. The first principal components used in PLS-PM.	Dimensionality of the consumer characteristics blocks.
GPA			Similarities among the liking variables and among the products.		
Standard multivariate regression	Consumer segments related to consumer characteristics (PLS, PLS-DA). On raw data for comparison (PLS).	PREFMAP by PCR, taking the residuals' averages over extrinsic variables.	MDPREF by PCR for each liking modality. Relations between liking scores (LM).	Liking data related to all the consumer characteristics (PLS).	
PLS-PM				Two approaches proposed to relate product, consumer and acceptance information.	
PM by SO-PLS					Study of several features on the basis of approach two in paper IV.
Fuzzy clustering		Different solutions tested to identify groups with similar response to intrinsic and extrinsic attributes.			
Pre-processing	Double-centered data. Standardisation prior to PLS-DA.	Consumer centered acceptance data. Double- centered for studying individual differences.	Standardisation for relating different liking modalities.	Consumer centered acceptance data. Standardisation of product, consumer and acceptance information.	Consumer centered acceptance data. Standardisation of product, consumer and acceptance information.
Validation	CV. Explained variance of the PCA components. Jack-knifing for variable significance in PLS-DA.	CV. Explained variance of the PCA and PCR components.	CV. Explained variance of the PCA and PCR components.	CV. Explained variance of the PCA components. Bootstrap to assess parameter estimates.	CV. RMSEP to choose the optimal number of components.

Table 1. Overview of the statistical methods used in the papers.

3.1 Mixed Models

The mixed model for the Analysis of Variance (ANOVA) allows the total variance to be partitioned into components related to different sources of variation. In this thesis the general approach considered is based on distinguishing two parts, one part including all main factor effects and their interactions as fixed and a second part expressing the individual random effects and their interactions with the fixed effects. In this context the consumer effect is assumed random because the individuals are deemed as representative from the consumer population. With two design factors, the model can typically be written as:

$$y_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + C_k + \alpha C_{ik} + \beta C_{jk} + \varepsilon_{ijk}$$

where y_{ijk} (*i=1,…,I, j=1,…,J, k=1,..,K*) is the *ijk*$^{\text{th}}$ observation, μ is the general mean, the α_i's and β_j's are the main effects of the two factors and the $\alpha\beta_{ij}$'s are their interaction effects. The C_k 's represent the random main effects of consumers, the αC_{ik} and βC_{jk} the interactions between consumers and design factors and ε_{ijk} refers to the random noise. When the model includes categorical and continuous variables for predicting the response, the analysis becomes an Analysis of Covariance (ANCOVA).

In the present context, conjoint analysis (P. E. Green & Rao, 1971; P. E. Green & Srinivasan, 1978; Moskowitz & Silcher, 2006; Næs, Kubberød, & Sivertsen, 2001) is a methodology based on mixed models for relating product attributes to consumer acceptance.

Mixed models are in this thesis used for facing two main problems: to analyse both population averages and individual differences within the same modelling framework (paper I); to identify which of the extrinsic and the intrinsic product factors are responsible for the consumer acceptance (paper II). ANOVA has also been used for calculating the main effects of product and consumer in path modelling (papers IV-V).

3.2 Principal Component Analysis

Principal Component Analysis (PCA) reduces the dimensionality of a data set of many interrelated variables, while retaining as much as possible of the variation in the original data (Jolliffe, 2002). This is achieved by the creation of a new set of variables, i.e. the principal components, which are uncorrelated and ordered in such a way that the first few components are the ones preserving most of the variation. The scores $\mathbf{T}$ for the principal components are calculated as linear combination of the response table $\mathbf{Y}$:

$$\mathbf{T} = \mathbf{YP}$$

with $\mathbf{P}$ being calculated as eigenvectors of the covariance matrix and expressing the principal component directions (Pearson, 1901).

In this thesis PCA has been used on sensory data, for profiling the products (papers II-III) and also for selecting the best possible subset of products to be combined with the extrinsic attributes (paper II). PCA can in addition be run on the matrix of specifically defined ANOVA residuals for displaying consumer individual differences (paper I). PCA has also been used on the liking values for extracting the components with most of the variability (paper IV) and on the difference values for highlighting differences between the acceptance of various sensory modalities and the overall liking (paper III). Finally, PCA has been useful for detecting the dimensionality of the consumer characteristics blocks (paper V).

3.3 Generalised Procrustes Analysis

The Generalised Procrustes Analysis (GPA) is a method that aims at reducing the differences between matrices, by means of translation, rescaling and rotation (Dijksterhuis, 1996; Gower, 1975). these transformations can be summarized in the following way:

$$\mathbf{D_i} + c_i\mathbf{Y_i}\mathbf{H_i}$$

where the $\mathbf{Y_i}$'s are the original data matrices, the $\mathbf{D_i}$'s are the matrices representing translation constants (eliminated with centered columns), the c_i's are the scalars representing the rescaling and the $\mathbf{H_i}$'s represent orthogonal rotation matrices. A criterion measuring the difference between the transformed matrices is then optimised and the average or the consensus matrix is computed.

The GPA is in this thesis used for measuring the similarities among different liking evaluations for sensory modalities ($\mathbf{Y_i}$ represents the data matrix associated to the liking modality i) for the different products (paper III).

3.4 Standard Multivariate Regression Methods

Regression methods focus on finding relations between data sets. The Multiple Linear Regression (MLR) relates the dependent to the predictor variables in the following way:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where $\mathbf{y}$ is the column of the response values for all the observed objects and $\mathbf{X}$ is the centered matrix of the *X*-variables. $\boldsymbol{\beta}$ is the corresponding vector of regression parameters and $\boldsymbol{\varepsilon}$ is the vector of random errors (Montgomery, Peck, & Vining, 2006;

Næs, Brockhoff, & Tomic, 2010). The aim in MLR is to find good estimates for the regression coefficients, which weight the importance of the predictors in explaining the response, to be used for prediction or interpretation.

In situations with many and possibly collinear variables, strategies of variable selection are employed in order to obtain data-compression and interpretable solutions. One of the most common techniques is the Principal Component Regression (PCR), which runs an analysis on the first few principal components of $\mathbf{X}$ that account for most of the predictors' variability:

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{\mathbf{T}} + \mathbf{F}$$

$$\mathbf{y} = \mathbf{T}\mathbf{Q} + \boldsymbol{\varepsilon}$$

where $\mathbf{X}$ and $\mathbf{y}$ are mean-centered predictor and response matrices respectively. In situations where the first few components $\mathbf{T}$ of $\mathbf{X}$ have less relation to $\mathbf{y}$ than the components explaining less variability, a good alternative to PCR is the Partial Least Squares Regression (PLSR). The only difference lies in the way the components are computed. The latter maximises the covariance between linear functions of $\mathbf{X}$ and linear function of $\mathbf{y}$:

$$\max\ cov(\mathbf{Xa}, \mathbf{yb})$$

This ensures that the extracted components are more relevant for the prediction of $\mathbf{y}$ than the principal components. For many response variables, the PLSR is often referred to as PLS-2; if the response is categorical, the method is named PLS Discriminant Analysis (PLS-DA).

In sensory and consumer studies the relations between sensory profiles (or other intrinsic product information) and consumer acceptance data are analysed by preference mapping (P.E. Green, Halbert, & Robinson, 1968). This method makes use of multivariate regression methods (PCR, PLSR) for explaining the consumer acceptance by the intrinsic product attributes (external preference mapping, PREFMAP) and vice versa (internal, MDPREF) (see e.g. Helgesen, Solheim, & Næs, 1997; Malherbe, Menichelli, du Toit, Tredoux, Muller, Næs, et al., 2013).

These multivariate regression methods have been necessary in the present thesis for satisfying various purposes: to investigate the relations between individual liking differences and consumer characteristics (paper I), to relate sensory attributes to the consumer liking by preference mapping (papers II-III), to detect drivers of liking (paper III). PLSR has also been used as reference method to be compared with the path modelling approach (paper IV).

3.5 Partial Least Squares Path Modelling

Partial Least Squares Path Modelling (PLS-PM) (H. Wold, 1979, 1985; S. Wold, H. Martens, & H. Wold, 1983) is an iterative algorithm that estimates the relationships among blocks of observed variables (manifest variables: MVs) through the construction of so-called latent variables (LVs). These relationships form a system of interdependent equations based on simple and multiple regressions (Betzin & Henseler, 2005; McDonald, 1996; Vinzi, Trinchera, & Amato, 2010). The PLS-PM comprises two models closely linked: a measurement model, explaining the relations between the MVs of the different blocks and their LV, and a structural model, relating the LVs in the different blocks to other LVs (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005).

PLS-PM is here used for proposing data structures and approaches that relate different blocks of consumers' characteristics to each other and to consumer acceptance (Olsen, Menichelli, Grunert et al., 2011) when product information is also available (paper IV).

3.6 Path Modelling by SO-PLS

The Sequential and Orthogonalised Partial Least Squares (SO-PLS) approach to path modelling (Næs, Tomic, Mevik, & Martens, 2011) estimates regression equations with N blocks of independent variables, i.e.

$$\mathbf{Y} = \mathbf{X_1 B_1} + \mathbf{X_2 B_2} + \cdots + \mathbf{X_N B_N} + \mathbf{E}$$

where the **Y** is the matrix of dependent variables, the **X**'s are the different blocks of input variables and the **B**s are the regression coefficients. The method is based on splitting the process into a chosen sequence of PLS modelling steps for each dependent block versus the related predictive blocks. The approach includes two main parts. The first part is based on the SO-PLS method (Jørgensen, Segtnan, Thyholt, & Næs, 2004; Måge, Mevik, & Næs, 2008). This method first fits the output block $\mathbf{Y}$ to the first input block $\mathbf{X_1}$, thus identifying the column space of $\mathbf{X_1}$ that best fits the $\mathbf{Y}$**.** Then the same is done for the second input block, by fitting the estimated residuals to $\mathbf{X_2}$ after orthogonalisation with respect to $\mathbf{X_1}$ (i.e. with respect to the extracted PLS component scores of $\mathbf{X_1}$ for the first model). The algorithm alternates PLS regression and orthogonalisation steps for all the blocks. Then the Principal Components of Prediction (PCP) method (Langsrud & Næs, 2003) is used in the second part since interpretation-driven and focused on the main variation in the output block that can be explained: the predicted **Y** values are used as input in a PCA.

The SO-PLS approach to PM has been used in this thesis and for the first time in experimental consumer studies in order to relate the blocks of consumers' characteristics to each other and to product information for understanding consumer acceptance (paper V).

3.7 Fuzzy C-means Clustering

The underlying idea of the fuzzy C-means (FCM) clustering algorithm (Bezdek, 1981) is that the natural tendencies of clusters in the data should be expressed by membership values. These values, varying between 0 and 1, can be interpreted as probabilities of membership to different groups (Krishnapuram & Keller, 1993). Indicating the membership values by u_{ij} and the distances by d_{ij}, the algorithm aims at minimising the following criterion:

$$J = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}^{m} d_{ij}^{2}$$

where $i = 1, \dots, N$ corresponds to the i^{th} object, $j = 1, \dots, C$ corresponds to the j^{th} cluster and m is an exponent called the fuzzifier parameter. Most often it is set equal to 2 (Krishnapuram & Keller, 1996), but other values can also be useful. The minimisation of *J* with respect to the membership values and the distances will favour combination of large values of u and small values of d and vice versa, corresponding to obtaining as clearly separated clusters as possible (Berget, Mevik, & Næs, 2008).

In this thesis the FCM is used to identify groups of consumers with a similar response from both the intrinsic sensory data and the extrinsic attributes (paper II).

3.8 Further considerations

Pre-processing

Scaling differences in the assessors' or consumers' evaluations should be considered as nuisance factors. It has been shown (Næs, 1990; Romano, Brockhoff, Hersleth, Tomic, & Næs, 2008) that a different use of the scale can have a considerable impact on the effects taken into account for explaining consumer acceptance. The data should thus be pre-processed prior to analysis, whether linear models or multivariate and multi-block techniques are used.

Scaling differences can incorporate two different aspects, namely differences in mean and in range (Næs, Brockhoff, & Tomic, 2010). The mean difference can easily be corrected by averaging the scores over consumers for each of the products. The effect of mean centering for each consumer means that additive differences between the consumers have been eliminated. In ANOVA studies, this is automatically done when the consumer effect is included in the model (Lea, Næs, & Rødbotten, 1997). Automatic centering is also done in case of preference mapping studies (Helgesen, Solheim, & Næs, 1997; McEwan, 1996; Måge, Menichelli, & Næs, 2012; Schlich & McEwan, 1992) and generally when the acceptance data are organised with products as rows and consumers as columns (see e.g paper III).

In some cases it may also be useful to center acceptance data in the other direction, i.e. across the products tested. If already centered for each consumer, then the data set becomes double centered. Double centering leads to an analysis of the relative differences between the consumers in their assessment of the different products, after the product effect has been eliminated. In this thesis it will be shown (paper I) that double centered values from a saturated ANOVA model (i.e. a model accounting for all the possible main and interaction effects for the conjoint factors) correspond to the ANOVA residuals. The residual values will contrast consumers with different pattern when compared to the average liking for each product (papers I-II).

When different scales are used for the different variables and when the method is not scale invariant, it is also important to standardise, i.e. to subtract the mean and to divide by the standard deviation. In the present thesis standardisation is used prior to PLS-DA (paper I), in regression analysis for studying the relations between different liking scores and thus for obtaining comparable regression coefficients (paper III), in path modelling studies for relating product, consumer and acceptance variables (papers IV-V). For the other studies, no standardisation is done, meaning that differences in variability are considered meaningful information.

Validation

Before the model is released to the user, validation is essential to determine the prediction ability of the computed equation and to assess the parameter stability (Næs, Isaksson, Fearn, & Davies, 2002). The simple comparison between the fitted model and the raw data leads to overoptimistic results, since the data used for fitting the model will always fit better than new data. In principle, the best way to validate the model is to compare it with the real behaviour of consumers, but this is difficult and based on the reliance in consumer ratings. Models from consumer data are also generally low in validated explained variance (Næs, Lengard, Johansen, & Hersleth, 2010) because of large random noise and extreme diversity between consumers.

The collection of new data by using new consumers is the most effective way to validate the model predictions. Prediction testing (H. Martens & Næs, 1989; Montgomery, Peck, & Vining, 2006; Næs, Isaksson, Fearn, & Davies, 2002) is a technique based on splitting the data set into two parts, one used for estimating regression parameters (calibration) and the other for validation. In this context, with a limited consumers' sample evaluating few products, prediction testing is not optimal since several observations are set aside for testing only (Næs, Brockhoff, & Tomic, 2010), thus it is not considered in this thesis.

When it is difficult to collect new data, cross validation (CV) is often applied to validate a model. Cross validation is similar to prediction testing since predictors are tested on data that are not used for calibration, but this is done by successively deleting observations from the calibration set itself. The procedure continues until all observations have been deleted once. The prediction ability can be calculated by the root mean square error of prediction RMSEP (H. Martens & Næs, 1989) of the predicted versus the measured values (see e.g. paper V).

In situations with a small set of samples based on experimental design, as is often the case in the present context, these validation techniques may be problematic to use: each sample is unique and may be difficult to fit into the model determined by the rest of the samples. In such cases it can be useful to look also at the predictive ability in X and/or Y (Næs, Brockhoff, & Tomic, 2010), expressed as per cent explained variance for each of the obtained components (see all the enclosed papers). A reasonable number of components can in some cases be chosen according to the explained variance plot by detecting a point where the curve is steep before and flattens out afterwards. Often there is a strong relationship among variables, thus only a few components are needed to explain a substantial amount of the total variance in the data.

It should finally be mentioned that other empirical validation procedures exist. External validity (H. Martens & Martens, 2001) is an important approach: a good argument for validity of the results is that interpretation makes sense in terms of previous knowledge. In a regression analysis, studying the variability of the obtained regression coefficients is useful for determining if they are stable and if their signs and magnitudes are reasonable (see e.g. paper III). Resampling by the use of Jack-knifing or by randomly drawing with replacement from a set of data points (bootstrap) (Efron, 1982; Efron & Tibshirani, 1993) is an important way of estimating variability in the context of consumer studies. Combined with information about model adequacy obtained by for instance residuals plots, these methods also shed light on the validity of the models. In this thesis Jack-knifing is used to evaluate the variable significance to the grouping information in a PLS-DA (paper I), while bootstrap is considered for assessing the variability of the parameter estimates in a PLS-PM study (paper IV).

4. LINKING AIMS AND METHODS

The insight into the relations between the available data blocks in the present context (sections 1.2-1.3) is attained by developing multi-block methodologies that analyse the data at three different levels (section 2.3). This section (and Fig. 6) will explain how the specific aims (section 2.1) are addressed in the papers by which statistical methods (section 3).

1) The study of the individual differences in acceptance pattern

The study of both average effects and individual differences in the same modelling framework is the focus of paper I. The strategy proposed for the conjoint case consists in performing a mixed-model ANOVA including all the fixed conjoint factors (main effects and interactions) and the consumer effect, but excluding interactions terms between consumer and conjoint factors. The rationale is that these residuals contain information about all individual interactions between consumers and conjoint variables and only that except noise. The residual values are double-centered and focus on the detection of each consumer's position relative to the other consumers for each of the products. Thus the ANOVA residual method leaves consumers' individual deviations from the mean consumer effect to further interpretation. PCA has been used on the residual matrix in order to highlight consumer differences in assessing products either higher or lower than the average consumer. In this paper focus is on *a posteriori* segmentation based on visual inspection of the PCA plots. Segments are thus chosen according to interpretation and focus of the study. Individual differences and segments determined in the proposed way are linked to the consumer characteristics by PLS-DA and PLS-2.

The investigation of individual differences by *a posteriori* segmentation strategies has also been accomplished in papers II and III. To further analyse the individual contributions when in presence of both intrinsic (principal components from PCA of the sensory variables) and extrinsic (additional product variables) information, in paper II the residual matrix is created in the way suggested in paper I. In this case, since categorical and continuous variables are included in the model, ANCOVA is used. In situations where different consumer groups tested different products (with different intrinsic properties), as is here the case, it is recommended to take the residuals' average over the extrinsic variables and to handle the obtained matrix with missing values by external preference mapping using PCR. Another proposed approach in paper II is to identify groups of consumers with a similar response to the intrinsic and extrinsic information by fuzzy C-means clustering. FCM is performed using a model based approach based on a linear model with extrinsic and intrinsic information. The segments are then analysed separately by ANOVA without using the individual contribution, since the consumers within the same group are already relatively similar.

In paper III consumer heterogeneity is analysed in various ways. First of all, in order to understand the individual differences in the relative weighting of the two specific liking attributes on the total liking, a simple linear regression analysis is run for each consumer separately. Thereafter a strategy for indicating which products are similarly or differently perceived by which consumers is proposed. The method is based on calculating the differences between total liking and each of the specific liking variables. Individual differences among consumers and the correspondence between the total liking and the specific liking values can then be elaborated through a PCA of the difference values. For each consumer, the interpretation is that negative centered values represent those products for which the specific liking has the most favourable value (among the products) as compared to the total liking. *A posteriori* segmentation is tested out in order to distinguish consumers with the strongest differences in their liking values. For illustration this is done by splitting the consumer group according to the first PCA component, which represents most of the variability in the data set. Plots of the average profiles in each segment for each liking variable offer an immediate graphical interpretation of the differences.

A priori segmentation is instead considered in papers IV and V, where the groups of consumers are directly defined by the consumer characteristics. Both papers take path modelling methodologies into account to better investigate how consumer characteristics of different origin (demographics, attitudes, habits and so on) relate to each other and to consumer acceptance, when product information is also available. In paper IV two different approaches based on PLS-PM have been investigated. The first approach focuses on the overall effects on liking of consumer characteristics and product variables, while the second approach focuses conceptually on the interactions between the consumer characteristics and the products. The latter requires an ANOVA prior to the PM for analysing the main product effects. Paper V explores the possibility of using the newly developed SO-PLS approach to PM for investigating how the different consumer characteristics are related to the individual acceptance pattern, based on the second approach recommended in paper IV. In both papers centering and standardisation are used, since different scales are considered for the different variables. Subtracting the mean for each consumer is also an important possibility if one expects this effect to be more related to the use of the scale than to information about individual differences. The second approach automatically uses double centered dependent variables if consumer centering is being used. For the first approach, however, consumer centering makes no sense (see paper IV for details).

2) Investigating the relations between product attributes and acceptance

Two different studies have been devoted to understand the main drivers of liking (intrinsic product attributes) and also how this intrinsic information can be combined to the extrinsic information (additional product attributes) for explaining consumer acceptance.

A new statistical approach to investigate the drivers of liking, i.e. to detect which intrinsic product properties influence the consumer acceptance the most, has been proposed (paper III). This is given by a combination of different methods and techniques that relate product blocks to the acceptance data set. First of all, a PCA of the sensory panel data is run in order to obtain insight into differences and similarities among the products. Then the plot of the average liking values for each product gives an indication of the possible differences among products for the different liking modalities. The internal preference mapping of each liking variable provides an additional valuable tool for understanding differences and similarities. GPA is then run for the purpose of comparing the scores from the different preference maps. Regression models that relate the total liking to the liking of the other sensory attributes are implemented to better understand the importance of each specific liking variable in explaining the total liking. Thereafter the differences between total liking and each of the specific liking variables are organised in a difference matrix and illustrated by PCA. PCR on the difference matrix shows which sensory properties characterise the differences between liking modalities.

When both intrinsic and extrinsic product attributes are available, it may be crucial to investigate their interactions when optimising product properties, even though this is seldom done and separate tests are run. How to combine intrinsic and extrinsic product attributes is the focus in paper II. The method is based on using different products for different consumer groups, but it ensures that the whole sensory space is covered as well as possible. For each consumer, each product is then combined with the same design in the extrinsic attributes, considered as categorical variables. For the analysis, two different approaches are appropriate. The first approach is to include both extrinsic (categorical) and intrinsic (continuous) product factors in a mixed model for the ANCOVA. The fixed effects contribution represents the average population effects and the random effect contribution accounts for individual consumer differences. The method focuses on the average population effects of both the intrinsic and extrinsic attributes, but an analysis of the individual differences (along the same lines as proposed in paper I) is also proposed. The second approach is based on fuzzy clustering using regression residuals. Since based on residuals, the method can be used also when the different consumers have tested different products, as they do in the case study of the paper. The method can find segments of consumers with a similar response to both the intrinsic and extrinsic variables.

3) The insight into consumer acceptance by means of both consumer characteristics and product attributes

The most complex level of relations between the data blocks represented in Figure 2 has been handled with path modelling methodologies. Two different approaches have been proposed, in order to organise the data blocks of different dimensionality, and tested through PLS-PM (paper IV). It has been shown that approach 1 (Fig. 4) focuses on the overall effect of the blocks of consumer variables as well as the design on the liking.

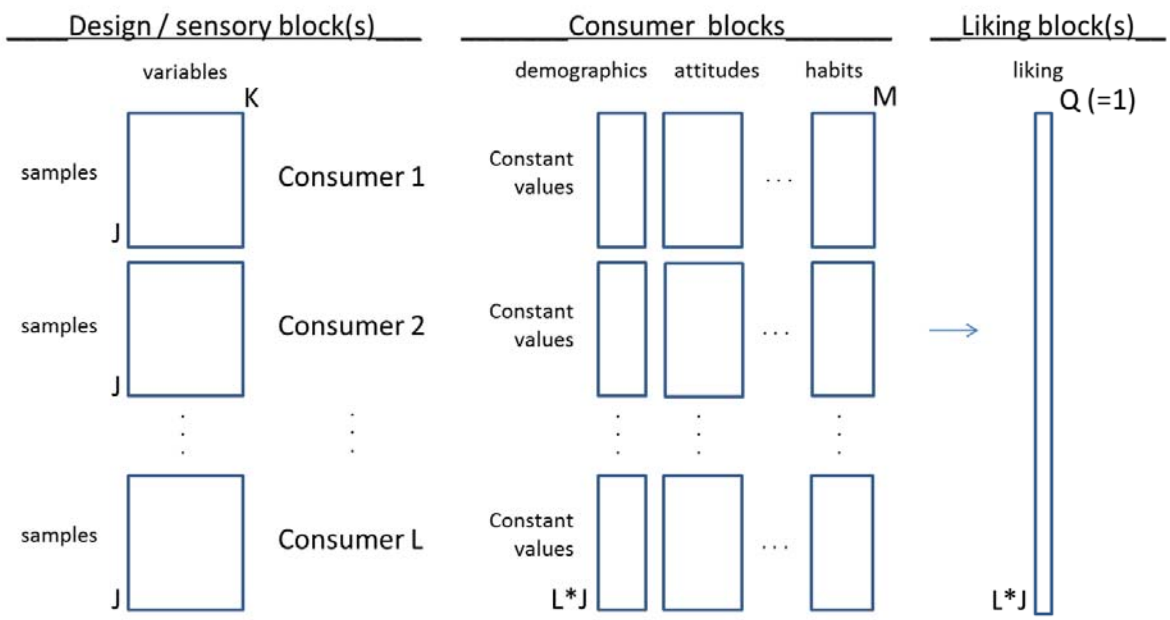

Figure 4. A graphical illustration of how the data sets are organised for approach 1. The liking block includes one single variable of length L*J, with L being the consumers and J the products. If more than one liking variable is available, Q blocks are considered as separate blocks of dependent variables. For the consumer characteristics' blocks each response for each consumer is repeated J times. The product data are likewise organised as an L*J times K matrix, with the K product variables (consisting of J rows) repeated L times.

In practice, however, it is not always likely that a consumer group has a liking that is systematically above or below the average for all products. A more interesting aspect to consider is linked to the interactions between the consumer characteristics and the products, i.e. how the different groups perceive differences between the products. Approach 2 (Fig. 5) focuses directly on these interactions. The reason for this is that each consumer characteristic will have a separate effect for each of the products. Since the second approach focuses only on differences in liking pattern, the ANOVA is required for analysing the main product effects.

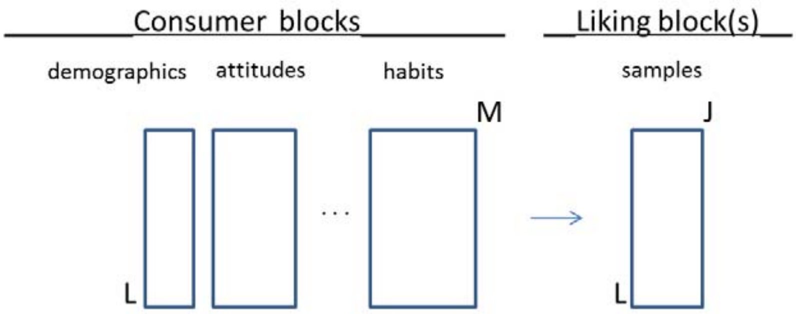

Figure 5. A graphical illustration of how the data sets are organised for approach 2. The consumer characteristics data set has dimension L*M, with as many rows as the number of consumers and with columns given by the M consumer characteristics. The liking data can be organised in different ways. The first alternative is in a L*J matrix, with L consumers as rows and J products as columns (as here depicted), but only if the block is uni-dimensional. The second alternative is to have J response blocks, each one containing the liking values of each consumer for the specific product. The third alternative is to organise the liking data in A blocks related to the first A principal components from PCA of the liking values.

This two-step procedure, namely first ANOVA and then PM, has also been considered in paper V for exploring the possibility of using the SO-PLS approach to PM in consumer acceptance studies, which has never been done before. This approach is based on the multi-block SO-PLS regression method. The method is based on sequential use of orthogonalization and PLS regression and results in an estimated regression equation and various interpretation tools for the different blocks in relation to the response acceptance block. When used in path modelling, the SO-PLS method is used independently for each endogenous block of consumer characteristics. For each regression model, once the predicted values are estimated, the PCP method uses these values as input to a PCA, so that focus is on the main variation in the dependent block that can be explained. Focus is also on how the method handles multidimensionality of the blocks and how it can be used to create blocks with a broader interpretation than in PLS-PM, such as for instance consumer habits, attitudes and demographic variables. It has been shown how this can simplify the analysis, at least for explorative purposes, as compared to other more traditional analyses.

In both paper IV and V considerations about centering and standardisation have been done when a path modeling approach is applied to blocks of data of different origin and dimensionality. Details about how to treat the different scales used for the different consumers', product and acceptance variables in a path modeling context can be found in paper IV.

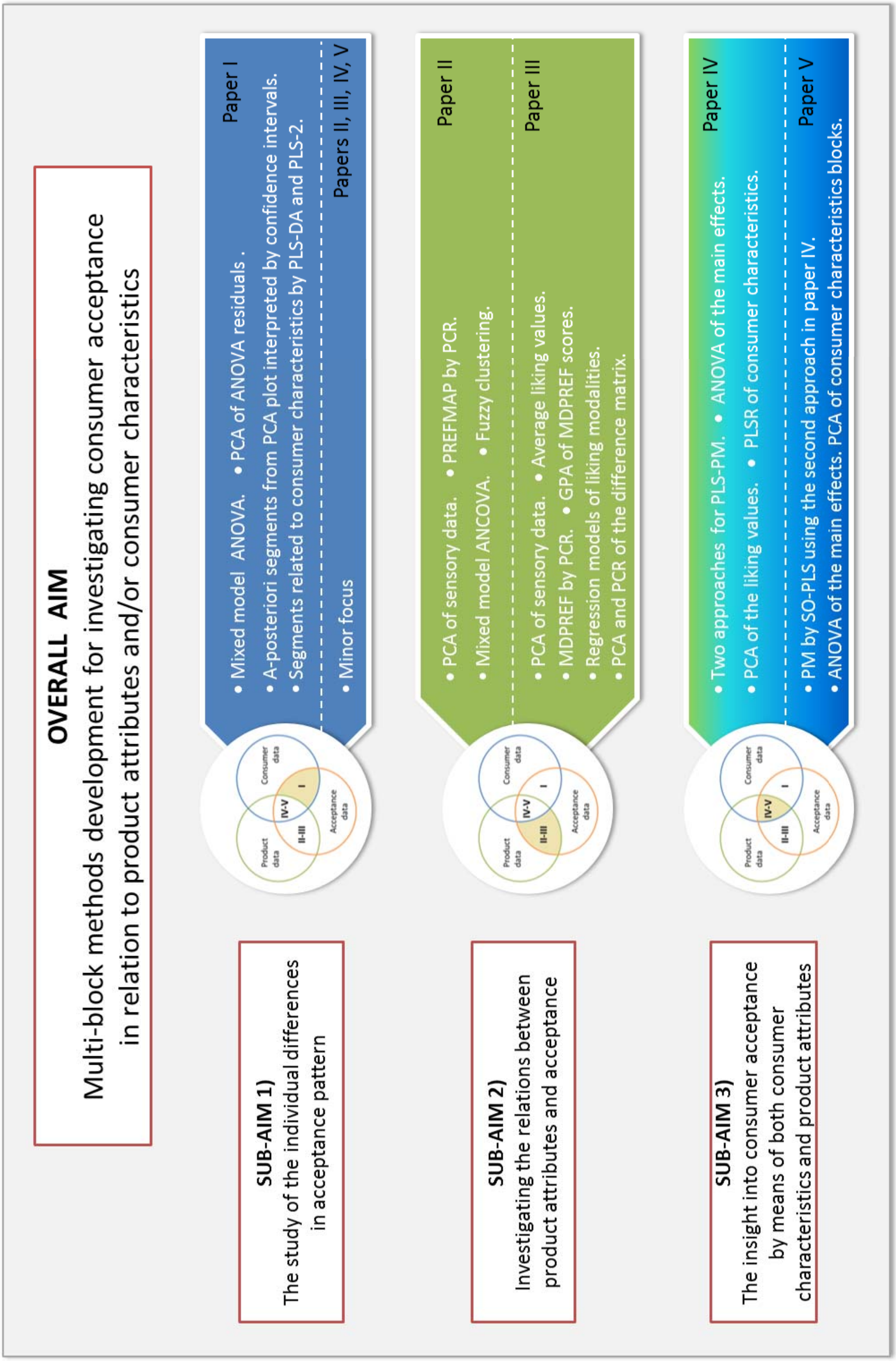

Figure 6. The link between aims and methods in the different papers according to the research strategy in section 2.3.

5. PAPER SUMMARIES

Paper I

In this paper the main objective is to present a method for analysing both population averages and individual differences in conjoint studies. The investigation of consumer heterogeneity can reveal differences between groups of consumers, even though the average likings for two products are the same. The methodology consists of two main steps. The first step is based on an ANOVA model that incorporates all relevant main effects, interactions and an additive consumer effect (fixed effects) and models the individual random error as a sum of various interactions between the consumer and the conjoint factors. Thus the residuals contain all possible components of the individual differences. The next step consists in organising the residuals in a matrix with the samples as columns and the consumers as rows. A PCA is run on these data and the scores and loadings plot analysed. The residual values can thus be interpreted as the consumers' ''distance'' to the average consumer liking for that product. Those consumers with a positive residual value for a product, score that product higher than what does the average consumer and vice versa. The splitting of the consumer group into segments with different liking patterns for the products is then interpreted by using confidence intervals for the different effects. Another possible way of interpreting individual difference is given by the visual segmentation (or a more automatic segmentation method, if applicable) and the relation between the segments to consumer characteristics by a suitable regression model. In the paper the approach is illustrated using two data-sets from consumer studies of yoghurt and apple juice.

The method handles average estimates and individual differences within the same modelling framework. Individual differences are easily interpreted and related to consumers' characteristics. The method is flexible with respect to the number and type of consumers' characteristics and can thus be used for categorical as well as continuous highly collinear variables. The last part of the study is graphically oriented to make interpretations easier.

Paper II

The study aims at combining extrinsic and intrinsic attributes in consumer testing of food products. Most often the two types of attributes are treated separately; this method is one of a few existing alternatives that can be used for joint studies. The general situation is that one does not know in advance if there are interactions between the two types of attributes and therefore this approach presents an important opportunity to detect them. The challenges related to the design are to select the best possible subset of products to be tested and to combine them with extrinsic attributes in a simple way. From an analysis point of view the main challenge consists of combining the large set of collinear sensory attributes with the extrinsic attributes. The method is thus based on using different products for different consumer groups, but it ensures that the whole sensory space is covered as well as possible in such a way that both linear and non-linear models for the sensory attributes can be used, at least at a population or average level. The principal components of the sensory space are then combined with the extrinsic attributes in a full factorial design.

For the analysis, two different approaches are appropriate. The first is to use a mixed model with a fixed effects contribution representing the average population effects and a random effect contribution accounting for individual consumer differences. The other approach is based on fuzzy clustering using regression residuals. The method is designed for finding segments of consumers with a similar response to intrinsic and extrinsic variables. The methodology is applied on a data set from a consumer study on choice probability of orange juices, tested in combination with information about price and production process.

Extrinsic consumer attributes are easily and efficiently related to the sensory properties of products, allowing for interactions. Emphasis is given on the whole sensory profile and the main drivers of liking. The methodology estimates population or segment means and gives an overview of individual differences in acceptance pattern. The method is general and can be applied to other situations in consumer studies. The methodology is relatively simple and is a combination of established methods, available in standard software packages.

Paper III

The objective of this article is to present a new statistical approach for the study of consumer liking. In general a possible problem with methods seeking drivers of liking is that both the sensory data and the consumer liking data are totally dependent on the actual products used in the analysis. Moreover the standard methods do not provide information about the importance of the different aspects of the liking. A possibility is thus to ask consumers to evaluate both the total liking and the liking of different attributes of the products. This approach will also depend on the actual products considered, but can provide additional information about the drivers of liking. First of all, sensory profiling by PCA and a plot of the average liking values provide a basic understanding of the sensory and liking data. A PCR of the relations between the sensory data and each liking variable and GPA on the obtained scores are then considered in order to achieve a more precise measure of the relative differences between the liking variables and between the products. Regression is also used for analysing how the different consumers vary in their weighting of the more specific variables when they assess the total liking. The next steps focus on the difference between total liking and the liking with the strongest discrepancy. One can thus identify those products and those consumers for which the liking of the specific property and the total liking are most different. Segmentation is finally tested out to distinguish consumers with the strongest differences in their liking values. The approach is illustrated by a case study based on cheese data. In the test consumers were asked to evaluate their total liking, the liking for texture and the liking for odour/taste.

The presented methodology identifies products and consumer combinations for which the different liking variables show a different pattern. The study demonstrates the potential of a methodology based on standard tools such as PCA and regression. Focus has been on the relation between average results and individual differences. The study relies on graphical representations and suggests some possible paths for further product development that are difficult to reveal based on the standard methodology of preference mapping.

Paper IV

The main aim of this paper is to relate different blocks of consumers' characteristics to each other and to consumer acceptance, when product information is also available. In consumer studies the data are often of a different nature (demographic variables, attitudes and habits). Usually, these data are considered together (e.g. by means of PLS regression) when modelling consumer acceptance patterns, even though there may exist interesting relations between groups of consumer characteristics. One may thus be interested in a deeper insight in how the different consumer characteristics relate to each other and in whether an effect is direct or indirect (i.e. works through another variable). This type of insight can be obtained by using path modelling and does not seem to have been tested in this context before. This paper proposes two different approaches for incorporating different blocks of consumer characteristics information. The data sets have very different structures and dimensionalities and it is not obvious how to combine them in such a multi-block context. The main focus is therefore on how to combine data sets with different columns and rows in a path modelling framework, how to pre-process data in the different cases and how to interpret the relations. The first proposed approach focuses on the overall effects on liking of consumer characteristics and product variables, while the second approach focuses conceptually on the interactions between the consumer characteristics and the products. Considerations about advantages and limitations are given. The different approaches are illustrated by data from a consumer test on chocolate, comprising several types of information about consumers.

Two approaches are proposed for incorporating blocks of consumer characteristics information in a path modelling framework, along with product attributes and acceptance. The second approach is recommended: this has been shown to give insight into the relations between types of consumer variables and also interpretative advantages in understanding acceptance patterns, since it takes into account that different consumer groups can have a different liking for the different products.

Paper V

This paper presents the new path modelling approach using Sequential Orthogonalised Partial Least Squares regression within the context of consumer science. The method is based on splitting the process into a sequence of modelling steps for each dependent block versus its predictive blocks. The estimation method is based on sequential use of orthogonalisation and PLS regression and benefits from a number of advantages. For instance, the method is invariant to the relative scaling of the blocks, it allows for blocks with several components, it can easily handle collinearity and it can be used for determining the additional contribution of new blocks that are incorporated. The interpretation is based on the Principal Components of Prediction (PCP) method but the different PLS regression models obtained can also be interpreted. The method provides various advantages that are related to simplicity and not relying on unrealistic assumptions. Main emphasis is given on how the method can be used to combine individual variables or specific groups of variables in more general blocks with a broader interpretation, such as consumer habits, attitudes and demographic variables. It is explored how the method handles multidimensionality of the blocks and thus how the analysis is simplified, at least for explorative purposes, as compared to other more traditional path modelling approaches. An application based on a consumer test on iced-coffees, including very different types of consumer characteristics, is used as illustration.

The SO-PLS approach to PM handles well the different types of information that are typical in experimental consumer studies. The advantage of creating blocks that can be interpreted in a broad sense, without any assumption of unidimensionality, enhances and simplifies the study. The possibility of using more than one dimension in each block also implies that the same dimensions are not necessarily used for prediction and to be predicted. The study shows that important relations are revealed in presence of both product attributes and consumer characteristics for investigating consumer acceptance.

6. DISCUSSION

Discussion of paper I

In this paper we present a method for analysing both population averages and individual differences based on the model residuals within the same modelling framework. The study is easy to interpret, flexible with respect to the number and type of consumer characteristics used and can be used for categorical as well as continuous highly collinear consumer characteristics. A similar approach based on PCA of the residuals was discussed in Hersleth, Lengard, Verbeke, Guerrero, and Næs (2011) but in the present paper the method is developed and various ways of handling, visualising and interpreting the individual differences in terms of additional consumer characteristics are illustrated. The general influence of the conjoint factors and the incorporation of categorical consumer characteristics have already been studied, but here it is shown that more detailed information can be extracted. The individual differences are studied in a different way than in preference mapping (McEwan, 1996). For preference mapping with only centering of the consumers, focus is on the relative differences in liking between the products. For the ANOVA residual approach, both the difference in level between the consumers and the average differences between the products are eliminated. This means that one concentrates on how the different consumers relate to the average consumer for each product, without considering the average product liking. The method is not meant to replace other analyses for individual differences, but merely to provide an additional tool which is more targeted at relative differences between consumers. The use of PCA in conjoint analysis is useful for looking at different types of segments based on visual inspection of the plots. An important argument for segmentation by visual inspection is that segments can be chosen according to interpretation and focus of the study. In both examples in the paper, the clusters are also validated by external consumer attributes and results were reasonable and as expected. Another argument is that automatic segmentation is very method dependent. Automatic clustering procedures (Mardia, Kent, & Bibby, 1979; Næs, Brockhoff, & Tomic, 2010; Vigneau & Qannari, 2002) may be used, nevertheless in this context there is always a continuum of individual differences with no clear separation between them. Automatic segmentation approaches, developed in other contexts, may therefore be somewhat questionable.

Discussion of paper II

The novelty of this paper relates to the valuable insight one may get from a joint study of intrinsic and extrinsic product attributes. This methodology presents an important opportunity to detect their possible interactions, which are usually unknown. Very few studies have been conducted where consumers are given food samples together with additional information (Johansen, Næs, Øyaas, & Hersleth, 2010; Stefani, Romano, &

Cavicchi, 2006; Urala & Lähteenmäki, 2006; Visschers & Siegrist, 2009). These studies mainly consider a number of fixed samples and draw conclusions more related to differences between the actual products than to the drivers of liking, without highlighting the effects of the whole sensory profile, its influence on the consumer preferences and possible interactions with the extrinsic attributes. The method proposed in Johansen, Næs et al. (2010) is innovative and useful but considers only corners of a rectangle in the sensory space, therefore only linear models can be used. Information from the whole sensory space can instead enable the use of others than the linear models, for instance ideal point models (Næs & Risvik, 1996). Such models are typically quadratic polynomial models in the principal components of the sensory data, with the ability to identify both negative and positive peaks in the liking pattern. The method in paper III uses instead different products for different consumer groups in such a way that the whole sensory space is covered as well as possible, thus non-linear models for the intrinsic information can also be considered. Also, note that since the different consumers can test different products, the amount of material needed for each of the products is less than if all consumers tested all of them. This may for instance be an advantage in studies involving products that for some reason are difficult to provide in larger quantities. The approach could also find application in consumer studies where the focus is different from linking sensory and extrinsic attributes, for instance combining numerical and categorical attributes (e.g. both being extrinsic).

Discussion of paper III

A general drawback with standard methodologies seeking drivers of liking is that the collected data are dependent on the actual products and conclusions may change if those products are replaced by new ones. Moreover, information about the importance of the different aspects of the liking is not provided. A trained panel produces a large set of attributes, but it is not obvious that all these attributes are relevant for the consumers. The proposed methodology in paper III still depends on the products used in the study, but provides valuable additional information about the most important aspects of liking. This enables the identification of possible alternative combinations of attributes with a potential for an even higher liking. Results may thus propose possible ways of improving the product properties, as shown in the case study based on cheese data. In addition, individual differences have not previously been studied in connection with relative differences among products when the liking for different sensory modalities has been in focus. This study has shown that, even though a specific liking for two products is the same on an average level, two groups of consumers can have evaluated them completely differently. From this and previous works (Moskowitz, 2001; Moskowitz & Krieger, 1993, 1995) it is clear that liking definitely is multidimensional. Despite the lack of sufficient literature on the topic (Moskowitz, 2001), the choice of broad sensory categories seems to be more advisable than many redundant liking ratings that consumers cannot discriminate.

Discussion of paper IV

When in an experimental consumer study the consumer characteristics represent different features, the main difference between using standard regression or SEM approaches is that the consumer characteristics are for the latter organised in blocks, with each block being a collection of related characteristics. This means that it is possible to link the consumer blocks to each other and to the liking blocks, allowing for estimation of both direct and indirect effects (Bollen, 1987, 1989). Standard regression on the other hand considers all the explanatory variables in a parallel way, thus it does not provide a direct measure of the relations among them. Interpreting the regression plots may give an idea of the relations between consumer variables through the variables' proximity in the space, but this is difficult when there are many variables with possibly strong inter-correlations between them. In addition, variables from one single block may be absorbed into different dimensions.

There exist different approaches to model estimation in path modelling, but in paper IV PLS path modelling (PLS-PM) is used for illustration. It is important to emphasise that the methods proposed in this paper (and also in paper V) for organising the data are applicable regardless of the possible ascription of causality to the path relations (M. Martens, Tenenhaus, Vinzi, & Martens, 2007; Næs, Tomic, Mevik, & Martens, 2011).

It should be mentioned that there are some considerations that have to be done prior to the analysis, such as a proper specification of formative and reflective modes, the satisfaction of the unidimensionality assumption for the reflective blocks and the pre-processing. Details and recommendations can be found in the paper, further aspects concerning double-centered data are included in paper I. It should also be mentioned that generally the relations between consumer characteristics and liking pattern may be quite weak (Næs, Lengard, Johansen, & Hersleth, 2010). Therefore, the type of relations that will be considered in this type of studies can seldom be used for any meaningful predictions, but only for estimating tendencies in the population. In this paper the main emphasis is thus on interpretation based on plots and regression coefficients assessed by the bootstrap method.

Discussion of paper V

The SO-PLS to PM has a number of advantages that can simplify the analysis in consumer studies. It does not require any investigation of unidimensionality of the blocks, thus it is possible to consider also blocks with a broad interpretation like demographics, consumer habits and attitudes. The method allows for situations where the variability predicted in a block is not necessarily the same as the part of the same block used for prediction of another block. This has been shown in the case study of paper V and is an additional tool to better interpret data and results. The method is also invariant to the relative scaling of the blocks, can be used for many variables and few observations and has no problems with collinearity among the variables within a block. Interactions between blocks can, if wanted, be incorporated (Næs, Måge, & Segtnan, 2011). Note that, since the second approach in paper IV is used here, focus is on the interactions between consumer characteristics and products.

Another feature of this method is related to the concept of "additional effect", i.e. the effect of adding a block to the model. The concepts of total, direct and indirect effects introduced by the SEM theory (see e.g. paper IV) are not available here. There also exist other standard SEM concepts that are not defined here, such as the measurement and structural models. Within the measurements model there is no distinction between formative and reflective modes (Addinsoft, 2012; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005; Vinzi, Trinchera, & Amato, 2010). Since PLS is used for estimation in the SO-PLS, all blocks can be considered reflective; if the maximum number of components is chosen, the block is fitted by LS regression and can thus be considered formative (Næs, Tomic, Mevik, & Martens, 2011).

Finally, the SEM methods have the advantage that they give one model containing all the blocks. The SO-PLS approach is instead considering one model for each endogenous block. Each model can anyway be simplified by the use of PCP, as shown in this paper. In situations with too many blocks, one may also consider to merge some of them prior to the analysis.

The SO-PLS approach to PM is interpretation oriented, but interpretation is done in models which are developed with as good prediction ability as possible. In paper V important relations between consumer, product and acceptance information are revealed. The interpretations obtained from this method are thus particularly useful for explorative consumer studies in an early stage of investigation of a complex system.

7. PRACTICAL IMPLICATIONS FOR THE INDUSTRY

The proposed multi-block methodologies have been developed by diving into the food industry's need of product and consumer insight. The studies included in the present thesis provide tools for relating different types of information and also recommendations to the food industry for developing successful marketing strategies through their use. In particular:

- It is important to understand the effect of a number of product factors on consumer acceptance by identifying both general tendencies in the populations and individual differences between consumers. This can easily be done with the ANOVA residuals method explained in paper I, where the population averages and consumer heterogeneity are analysed in the same modelling framework. The possibility of understanding the individual differences in terms of consumer characteristics provides additional information for successful strategies of market segmentation.

- Investigating intrinsic and extrinsic product attributes in independent tests may be insufficient and a technique that can simultaneously analyse and detect possible interactions between intrinsic and extrinsic attributes for explaining consumer acceptance may be highly relevant in concrete industrial product development situations. An additional advantage of the method in paper II is that it can possibly be used for better linking data from development departments in a company. Typically the sensory analysis and preference mapping are conducted in the product development department, while conjoint studies related to extrinsic attributes are implemented in the marketing or public relations department, often by people with different backgrounds and traditions. The use of joint studies is a possible way of bringing two important areas of expertise more closely together.
- Information about drivers of liking may enable the product developer to increase the consumer liking. The method suggested in paper III enables understanding of the overall liking in terms of the liking for the specific sensory modalities and suggests possible paths for further product development by identifying combinations of attributes for an even higher liking. This insight is difficult to achieve through standard methods like preference mapping.
- The collection of data about different types of consumer characteristics can be used for the insight into their relations and also to benefit from advantages in interpretation and understanding of the acceptance pattern. In paper IV and V it has been shown that different consumer groups can have a different liking for the different products. Both studies can be applied in preference mapping, conjoint studies and also in a combination of the two. They are thus valuable tools for the industry for understanding direct, indirect (paper IV) or additional (paper V) effects for the consumer characteristics on the acceptance, when also product information is available. It is recommended to use the SO-PLS to PM (paper V) for explorative purposes, since the main tendencies are revealed and the analysis is simple and fast. PLS-PM (paper IV) can instead be considered for a more confirmative analysis based on results previously obtained.

All the methodologies are simple, transparent, flexible, graphically oriented and easy to reproduce in standard statistical software packages. In addition, a free and open source software, the ConsumerCheck software, will soon be available (end of 2013) as a user-friendly tool helpful to industries and anyone interested in carrying out data analysis strictly related to the methodologies presented in this thesis.

8. CONCLUSIONS AND FUTURE PERSPECTIVES

This thesis contributes to the field of sensometrics in general and to the multi-block methodologies for experimental sensory and consumer studies in particular. The aim of the thesis is to develop methods for investigating consumer acceptance in combination with product attributes and consumer characteristics. Typically independent analyses are done, excluding possible important relations between the different sources of information. The methodologies in the thesis have been advanced in order to detect these relations.

Individual differences have been a main focus throughout the thesis and important strategies for both *a priori* and *a posteriori* segmentation have been developed. In particular the first paper contributes to this type of insight. Very recent results (Endrizzi, Gasperi, Rødbotten, & Næs, 2013) indicate that the residual based method offers some simpler possibilities for segmenting consumers when interpretation based segmentation is used. This is still a new method and more research is needed for obtaining a full validation of its potential. An extension of the ANOVA residual method may be related to some considerations on consumer acceptance. Consumer liking may not only differ in relation to the product design and between the groups specified by the consumer characteristics. Also the heterogeneity within such groups can differ, i.e. consumers within a specific group may prefer products on either side of a conjoint factor. Such an insight may be an important basis for marketing strategies. Work is in progress to reveal systematic consumer heterogeneity of liking by expanding the mentioned approach.

Other methodologies are available for taking the information about products, consumers and acceptance into account. In particular the L-PLS method (H. Martens, et al., 2005) is a very interesting approach, but at present it does not provide any direct information about population effects and not all aspects of interpretations are investigated. In addition few applications have been reported (H. Martens, et al., 2005; Plaehn & Lundahl, 2006). Other L-based methods (Fig. 2 and Section 2.2) can be found in Lengard & Kermit (2006), Endrizzi et al. (2008) and Vinzi, Guinot & Squillacciotti (2007). Further research should be dedicated to comparing these methodologies to the ANOVA residuals method (detection of average and individual effects, transparency, ease in interpretation, …) and to the PLS and SO-PLS approaches to PM, which do not treat the consumer characteristics in a parallel way.

Possibilities for further method development can also be found in relation to paper II, where the approach for clustering was based on the extrinsic factors and the use of a sufficiently flexible model for the intrinsic attributes. If in the specific study one believes that the consumer group is a combination of subgroups with similar response pattern to all the attributes tested, one may also look at the intrinsic model for the clusters. There is, however, no way for the actual approach (with only three products to each consumer) that one can test the real fit of each consumer to a complex intrinsic model. If this is required, more than three products must be used. The methodology presented in paper II is based on an idea of an incomplete design in the sensory scores and the same design for the categorical extrinsic design variables. A natural question is whether it could be possible to introduce incompleteness for all the variables simultaneously, for instance in the case of large conjoint studies. Another possibility would be to use an incomplete design for each of the consumer groups that test the same samples. New method development would be required for these purposes. All these considerations show the dilemma when combining intrinsic and extrinsic attributes. Research should therefore focus on how to combine sample selection with an idea of incomplete design for the extrinsic attributes.

In paper III the drivers of liking where investigated by comparing pairs of liking scores. Further development may thus pertain to a simultaneous comparison of all the available liking evaluations, so that the calculation time can be considerably reduced and the methodology can be applied also in case of a large number of attribute liking scores.

Finally, all the papers account for consumer tests performed according to acceptance. The methods do not focus on preference evaluations, but can anyway be modified and extended to ranking or choice data (Almli, Øvrum, Hersleth, Almøy, & Næs, 2011; Campbell, 2007; Train, 2009). How to handle this the best possible way should be investigated further.

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PART II

PAPERS

Paper I

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Handling of individual differences in rating-based conjoint analysis

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ABSTRACT

In this paper a method for handling individual differences in conjoint analysis is described and discussed. This method is a combination of ANOVA and PCA/PLS both of which are well-known techniques that can be run in almost all statistical software packages. Main attention will be given to the way individual differences in acceptance pattern are interpreted and related to consumer characteristics such as demographics, attitudes and habits. The approach is then illustrated using two data-sets from consumer studies of yoghurt and apple juice.

1. Introduction

Conjoint analysis (Green & Srinivasan, 1978; Gustafsson, Herrmann, & Huber, 2003; Louviere, 1988) is a methodology for consumer studies which is suitable for studying the effect of a number of product factors on consumer acceptance, preference or choice. The methodology is based on designed experiments where the different factors are combined according to the number of factors chosen and the preferred size of the experiment. This creates a number of "prototypes" or products that are presented to the consumers. They give their scores of liking, rank the products or choose one among a number of alternatives in so-called choice sets (Louviere, 1988; Louviere, Hensher, & Swait, 2000). The data are usually analysed either by analysis of variance (ANOVA, see e.g. Næs, Lengard, Bølling Johansen, and Hersleth (2010a)) or by generalized linear models (McCullagh & Nelder, 1989; Nelder & Wedderburn, 1972). In the present paper focus will be on rating based methods.

In conjoint analysis both general tendencies in the population and individual differences between consumers are important. It is also crucial to understand the individual differences in terms of consumer characteristics related to demographics, attitudes, habits, etc. This is important for improved understanding of consumers in general, for product development and for development of good marketing strategies. Incorporating individual consumer characteristics in rating-based conjoint analysis can be done in various ways. One important option is to add consumer characteristics as factors in a joint analysis of variance (ANOVA) model of all the data (Næs et al., 2010a; Næs, Brockhoff, & Tomic, 2010b), thus obtaining a simultaneous estimation of conjoint factor effects, consumer group effects and their interactions. Another possibility is to use cluster analysis of the acceptance values and then link the clusters to consumer characteristics afterwards using some type of discriminant analysis. Multivariate analysis of the residuals from a simplified ANOVA model with only the conjoint factors present is another and related possibility suggested in Næs et al. (2010a and 2010b). A fourth possibility is to relate the acceptance values directly to the consumer characteristics using a full Partial Least Squares (PLS) approach (Næs et al., 2010a, 2010b)). A variant of this is to compute factor effects for each individual separately as sometimes done in conjoint analysis to obtain individual utilities, and then relate some of these effects to the consumer characteristics using regression analysis. Yet another possibility is to combine information about the design, the acceptance pattern and the consumer characteristics in one single analysis using either the L-PLS regression method (Martens et al., 2005) or cluster analysis (Endrizzi, Gasperi, Calò, & Vigneau, 2010), thereby obtaining information about acceptance values among different consumer groups directly in one single analysis.

In this paper we will discuss and extend the method of Næs et al. (2010a, 2010b) for analysing both population averages and individual differences based on the model residuals within the same modelling framework. The analysis of the population effects is identical to the standard ANOVA way of analysing conjoint effects and the analysis of the individual differences will be based on careful analysis of the ANOVA residuals by the use of PCA and PLS. The latter part is graphically oriented and easy to interpret

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and understand. The method also has the advantage that it is flexible with respect to the number and type of consumer characteristics used and can be used for categorical as well as continuous highly collinear consumer characteristics. All the steps in the approach can easily be handled within most standard software packages.

A similar approach based on PCA of the residuals was discussed in Hersleth, Lengard, Verbeke, Guerrero, and Næs (in press), but in the present paper we develop the method further and illustrate and discuss various ways of handling, visualising and interpreting the individual differences. In particular we describe the specifics of the method in more detail with respect to what is done and how the results are to be interpreted. The method will be contrasted to other approaches. In particular we will also show that the PCA approach based on the residuals gives the same results as a corresponding PCA analysis of the original data after double centring. We also highlight and advocate visual segmentation by the use of PCA plots and discuss in detail how to interpret the segments and how to relate the segments to external consumer attributes and the design of the study. Different aspects related to how this is done the best possible way for different types of consumer characteristics is also a major issue. Different ways of centring the data will be discussed and illustrated. The present paper can also be looked upon as a case study or an empirical demonstration of the flexibility of the method as well as its usefulness in more than a single case (Hersleth et al., in press).

The method will be illustrated by using data from two conjoint studies briefly described in Section 3. The two data sets are from consumer studies on yoghurt and apple juice. In both cases, the general influence of the conjoint factors and the incorporation of categorical consumer characteristics have already been studied, but it will be shown that more detailed information can be extracted if individual differences are treated as discussed here. The focus of the yoghurt study was on consumers' acceptance of yoghurt with different level of sweetness and richness given with different information about fat content and sugar content. The apple juice study is a study of the effect of different novel processing technologies on people's acceptance of the juices. The treatment attribute was combined with price and different juice quality. In both cases, a questionnaire was used to collect information about attitudes, habits, etc., for the consumers involved.

2. Methods

2.1. ANOVA model structure

The type of conjoint analysis discussed here is based on some type of experimental design, for instance a factorial or a fractional factorial design. For this type of data it is in most cases natural to use an ANOVA model (see e.g. Næs et al. (2010b)). Here we will concentrate on modelling all consumers simultaneously within the same framework.

The joint ANOVA approach to conjoint analysis is based on incorporating all relevant main effects and interactions for the population (fixed effects) and then model the individual random error as a sum of an additive consumer effect (random) and various interactions between consumer and the conjoint factors (also random). With for instance two conjoint factors, the model can typically be written as

$$y_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + C_k + \alpha C_{ik} + \beta C_{jk} + \varepsilon_{ijk},\quad i = 1,\ldots,I,\quad j = 1,\ldots,J,\quad k = 1,\ldots,K \tag{1}$$

where i, j refer to two different conjoint factors, k refers to consumer, y_{ijk} is the (ijk)th observation, μ is the general mean, the α_i's and β_j's are the main effects of the two conjoint factors and the $\alpha\beta_{ij}$'s are their interaction effects. The C_k's represent the random main effects of the consumers, the αC_{ik} and βC_{jk} the interactions between consumers and conjoint design variables and ε_{ijk} is the independent random noise. For previous analyses and discussions based on the same model we refer to Hersleth, Mevik, Næs, and Guinard (2003) and Næs et al., (2010a, 2010b).

The model (1) contains a fixed population part and a random individual component reflecting how the different consumers vary in their way of assessing product differences. In the approach proposed here we will first estimate and test the fixed population effects by regular ANOVA and then use the variance components of the random effects and the residuals from the fixed model fit to study the individual differences. The effects from the fixed part of the model can if wanted be combined to obtain the average utility values for the different factor combinations. The fact that both types of effects are analysed by the same model is mentally appealing since all aspects of the analysis then take place within one single model framework. As far as we know, no other approaches have this feature. The fact that the individual effects or the effects of segments of consumers can be superimposed in order to visualise differences between segments (Fig. 8) is also easy to understand and argue for within this framework.

The residuals used in this paper are obtained from a model with only conjoint factors and the additive consumer effect. With the consumer main effect in the model, the residuals using model (1) can then be written as

$$\hat{e}_{ijk} = y_{ijk} - \hat{y}_{ijk} = y_{ijk} - \hat{\mu} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\alpha}\hat{\beta}_{ij} - \hat{C}_k \tag{2}$$

Here the $\hat{C}$ is the estimate of the consumer effect in the model considering C as fixed. The residuals are, however the same regardless of whether the effect is assumed random or not. As can be seen, these residuals contain all possible components of the individual differences which above are modelled as interactions between the consumer and conjoint effects plus the random error ε from model (1). Note also that the residuals are mean centred for each consumer corresponding to correcting for additive differences in use of the scale as will be discussed below. When the fixed effects model is saturated (i.e. all possible interactions are incorporated) the residuals are also mean centred across consumer for each combination of i and j. We will only consider saturated models (for the conjoint factors) here, i.e. double centred residual data (see Section 2.2).

Note that essentially the same ANOVA model as (1) was used in Næs et al. (2010a) for providing residuals for analysis of individual differences. In that paper, however, only plotting of single residual vectors for each consumer was considered. In the following we will put main emphasis on PCA of the whole residual matrix and also on how to interpret the results, how to do segmentation and how to interpret the segments. Using PCA on this matrix was first suggested by Hersleth et al. (in press), but here we will investigate more deeply how to interpret the results, how to do the segmentation and also how to interpret the segments in terms of additional consumer characteristics. Different ways of doing this will be discussed and illustrated.

2.2. PCA for the individual residuals

The next step in the process (see also Næs et al. (2010a and 2010b)) is to organise the data set in a matrix with the different samples as columns and the consumers as rows. Then a PCA is run on these data (un-standardised, covariance matrix used) and the scores and loadings plot analysed. Main focus will here be given to two-dimensional PCA plots, but a discussion will also be given on how to extend to three dimensions and higher. For one of the data sets, also a segmentation for the third component will be considered. A standardised analysis could also be possible here, but since the residual values are on the same scale there is no strong reason for doing so.

The effect of mean centring for each consumer means that additive differences between the consumers have been eliminated. This additive effect may in many cases have a strong component related to different use of the scale. In the example section this effect will be studied and commented on in more detail. The effect of the fact that the residual matrix is centred also for each column is that for each attribute combination (each product), the residual values represent the consumers' "distance" to the average consumer liking for that product. Those consumers who have a positive residual value for a product, score that product higher than what does the average consumer and vice versa. The implication of this is that the PCA will highlight consumer differences in assessing products either higher or lower than the average consumer. In other words, the proposed procedure is particularly suitable for contrasting consumers with different pattern when compared to the average liking for each product, which is often what is wanted.

As always, the PCA axes should be interpreted by looking at the loadings. An interesting interpretation may for instance lead to a splitting of the consumer group (here PCA scores) into consumer segments with different liking pattern for the products. If segmentation is done in this way, we propose to present the results for each segment using confidence intervals for the different effects as illustrated in Section 4. This way of presenting the results will automatically visualise individual differences for different consumer groups in their response to the conjoint factors. It should be mentioned that since the sums for each row and each column are equal to 0, there will always be focus on contrasts. The focus should be on the magnitude of the effects and also what differences between products that are the most important at an individual level.

The actual group average values can be added to the average values obtained in the population in order to highlight the average acceptance values for the different segments in the same units as the raw data, as will be illustrated below (Fig. 8). Automatic clustering can also be used for segmentation, but since clearly separated clusters cannot be expected in this type of studies, we believe it is generally advantageous to segment according to visual inspection combined with the purpose of the study and knowledge and insight regarding the data. If wanted, one can do both as was done in Helgesen, Solheim, and Næs (1997).

In the interpretation of the loadings, i.e. finding the relation between the axes and the products, ANOVA can be used to enhance interpretation. A simple possibility is to use the loading values for the first and second component (separately) in the PCA as dependent variables and the design variables as the independent ones. With two design variables in the conjoint setup, the model for the loading along axis 1 could for instance be the following

$$L_{ij} = \mu + \gamma_i + \delta_j + \varepsilon_{ij}. \tag{3}$$

where L is the loading value for axis 1 and the γ and δ are the factor effects. The two effects refer to the same two phenomena as represented by α and β in model (1), but here they are used with another response and we have therefore decided to use different symbols. Note that in this approach no strict statement about significance should be made and that the results will only be used to improve visual inspection. The approach is then more similar to that used for understanding tables of results from statistical simulations (see e.g. Cederqvist, Aastveit, & Næs, 2005) than standard hypothesis testing.

2.3. Relating the residual pattern to consumer characteristics

Relating acceptance patterns to external characteristics can be done in various ways. One possibility is to relate the consumer scores (here residuals) directly to the external variables using regular PLS regression, which can easily handle a large number of highly collinear variables. Another possibility is to identify segments and relate the segments to the consumer characteristics using some type of discriminant analysis, either the simple PLS-DA (PLS discriminant analysis; see e.g. Barker & Rayens, 2003) or a more sophisticated method. The PLS-DA method is based on first creating a dummy matrix to define group or segment membership and then relating this data table to the consumer characteristics using standard PLS-2 methodology. Yet another possibility is to use tabulation as suggested in Helgesen et al. (1997).

When concerning the external characteristics, there are a number of issues to consider. The first one is whether one should use all of them at the same time or concentrate on groups of variables separately. Which approach to select depends on the number of variables and on their nature. If the number is very large it may be wise to concentrate on subgroups and try to understand each of them separately.

In some cases it may be wise to categorise a variable prior to the analysis (Næs et al., 2010a and 2010b). One such example could be age. If it is unlikely that age is linearly related to the acceptance pattern, one should divide age into categories and create dummy variables to indicate age group membership. This method is general and can be used for any variable that one suspects to have a non-linear relationship. If a variable is categorical or has been categorised, one will need to generate dummy variables to identify the classes.

If the variables involved are of very different scale, one should standardise prior to analysis. It may also be useful to mean centre across consumer characteristics for each consumer in order to eliminate possible scale differences. If this is done, it can be performed for all the relevant variables simultaneously, or for subgroups with related meaning.

If there are groups of characteristics that may be linked according to a causal pattern, it may even be possible to build this structure into the model and use some type of path model in the estimation (Martens, Tenenhaus, Vinzi, & Martens, 2007; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). For instance, demographic variables may influence attitudes and both may influence liking. This can provide information not only about which variable is important, but also in which way and how the different blocks of characteristics are linked.

Variable significance can be evaluated by the Jack-knife method (Martens & Martens, 1999). This is done by calculating the standard deviation of the coefficients using the jack-knife resampling method and then by comparing the actual prediction values by their standard deviation as in regular significance testing for regression. One should, however, be aware that if significance testing is done first and variables eliminated accordingly, the validation variance (obtained afterwards) may be overoptimistic. The advantage of using the PLS approach is that it gives characterisation of the groups in terms of the original variables through their position in the loading plot.

2.4. Comparison with other approaches

Note that the approach proposed here resembles what is done in standard internal preference mapping (McEwen, 1996) where also the main focus is on individual differences using a PCA approach. In the present case, however, the individual differences are studied after the general population structure has been subtracted, not on the raw data as done in preference mapping. This means that all values considered here are relative to the average population effects for each product. Larger values than zero are above the average liking for that particular product and smaller values are below. Another difference is that for preference mapping, the data matrix is organised with samples as rows and consumers as columns. This could also have been done in the present paper, but for double centred data as discussed here, the two results will be identical, the only difference is that scores become loadings and vice versa. Therefore, interpretation, etc. will be the same.

It should be mentioned that a PCA of the original data organised with consumers as rows and products as columns and after double centring will give the same results as the PCA described here. The reason for this is that when centering the raw data matrix for each column, the population effect of that sample is essentially eliminated, in the same way as when fitting the model and calculating the residuals. The present approach is, however, advantageous from an interpretation and understanding point of view since it links the estimation of population effects and the study of the individual differences more closely together. It also provides better arguments for the superimposition mentioned above and more direct motivation for subtracting the product means. In other words, the two methods (population fitting and segmentation) do not appear as two different approaches to the same data set, but are clearly two stages of the same analysis process. As far as we know the use of PCA in conjoint analysis is not common, at least not in the area of food science.

As stated above a simple way of incorporating external consumer characteristics in the model is to add these factors and their interactions with the conjoint factors to the model (1). This is simplest for categorical or categorised variables (Næs et al., 2010a), but it can also be performed with continuous variables if they have a reasonably linear relation to liking. These approaches will only give information about the average effects and it is difficult to use too many consumer characteristics at the same time both from a technical and interpretation (possibly due to high collinearity among them) point of view. If the conjoint factors are modeled as continuous factors, which may sometimes be natural if they have more than two levels, a mixed covariance analysis model should be considered (see among others Searle, Casella, & McCulloch, 1992, and McCulloch & Searle, 2001) as alternative to (1). We refer to Næs et al. (2010a) for further discussion of this point in a conjoint context. Note that this approach is more similar to what is called a priori segmentation (see Næs et al. 2010b) since one typically has to decide the consumer characteristic to use in the model and all results obtained will be based on these data. The approach proposed here, is however, more open and decides possible segments from the liking data without using any prior information.

Another way of analysing individual differences is to use a fixed ANOVA model for each consumer and afterwards do a meta-analysis of the individual effect estimates. They can for instance be plotted in histograms as done in Næs et al. (2010b). This may be useful for the purpose of estimating individual differences, but it gives no direct information about the population effects (and utilities). The second phase of this approach is typically to relate the profile of individual factor effects to external consumer attributes by the use of for instance PLS. This second part is structurally comparable to the present approach, but is different in the way the response data are defined. For further discussion of this method we refer to Næs et al. (2010a).

Another related approach is to just use the raw preference data for all products and related them directly to the consumer attributes by PLS regression. As for the method just described, this approach provides no direct information about the population, and one must rely completely on the results from the PLS plots. Since relations between consumer liking values and consumer characteristics is not always so strong, this approach may fail to reveal all the important information that is in the data (Næs et al., 2010a).

The approach proposed here is based on PCA plotting of the residuals and segmentation based on visual inspection of the plots. A major advantage of this is that one can look at different types of segments based on interpretation obtained from the plots. It is also our general experience that one very seldom finds totally separated clusters in this type of liking data and the results that can be obtained by automatic clustering methods will depend strongly on which clustering method is used. Therefore, visual interpretation has certain advantages that automatic methods do not have. In Hersleth et al. (in press) both approaches were used and in this case they gave essentially the same results.

Yet another possibility exists, the so-called L-PLS method of Martens et al. (2005). This is a type of methods which is based on taking both information about the samples, about consumer liking and about the consumer characteristics into account in the same modelling. This is an interesting approach from a mathematical point of view, but at the present stage of development there are still open questions related to how to interpret the results, in particular if there are strong structures in the consumer attributes and they have little relation to the liking. The method does not provide any direct information about the population effects. We think the method proposed here is more transparent with respect to what is done with the data and that it is also easier to interpret (at least at the present stage of development).

3. Data sets

3.1. Yoghurt data

This data set was used for studying the effect of information and sensory characteristics on consumer acceptance of yoghurt (Johansen, Næs, Øyaas, & Hersleth, 2010). A $2^{(4-1)}$ design with resolution IV was used. Two of the factors were product based (intrinsic) while the other two were related to information given to the consumers (extrinsic). The two product factors were related to degree of sweetness and richness and the two information factors were related to information about fat content and sugar content. The focus was on investigating the relative importance of the different factors.

In the study 153 Norwegian consumers were asked to rate their degree of liking on a modified version of the nine point hedonic scale by Peryam and Pilgrim (1957). After the consumers had rated the eight different combinations, they were asked to fill in a questionnaire related to socio-demographics, health and taste attitudes, as well as relationship to and use of yoghurt. In particular here we will consider age, gender, educational classes, product use and health and taste attitudes with basis in the Health and Taste Attitude Scales by Roininen, Lahteenmaki, and Tuorila (1999). For further details about the selection of products, how these deal with the actual characteristics and consumer test procedures we refer to Johansen et al. (2010).

3.2. Apple juice data

In this case the focus was on the effect of information about production technology on stated choice preferences for apple juice (Olsen et al., in press). The design used was a full factorial design with three factors of interest: production technology, taste and price ($4*2*2 = 16$ combinations). The first factor describes the process adopted for the production/storage of juices. Four processes are considered: six days in refrigerator (fresh juice), 1 year at room

Table 1
The subscale *general health interest* from the health and taste attitude scales by Roininen et al. (1999)[a].

Health1	The healthiness of food has little impact on my food choices ®
Health2	I am very particular about the healthiness of the food I eat
Health3	I eat what I like and I do not worry much about the healthiness of food ®
Health4	It is important for me that my diet is low in fat
Health5	I always follow a healthy and balanced diet
Health6	It is important for me that my daily diet contains a lot of vitamins and minerals
Health7	The healthiness of snacks makes no difference to me ®
Health8	I do not avoid food, even if they may raise my cholesterol ®

[a] Negative statements are marked with an ® after the statement.

temperature (juice treated with old method), 6 weeks in refrigerator (juice treated with two new production methods, HPP and PEF, see Olsen et al. (in press)). The second factor concerns the taste: two different local juices are considered called respectively standard and premium taste. The third factor has two levels: standard and high price (standard increased by 30%).

The test was conducted as an in-hall test with 154 Norwegian consumers who were asked to imagine that they were going to the store to buy apple juice. After this introduction the respondents were asked to read each of the 16 descriptions, which were presented in a randomized order, carefully, and indicate on a 7 point Likert scale, where 1 = "not very likely" and 7 = "very likely", how likely it is that they would choose these juices. The consumers were split in two groups. One of the groups tasted real samples and the other group only got verbal information. Information was thus incorporated as a separate factor in the analyses.

Then the consumers were asked to indicate their agreement with eight health statements from the "*General health interest*" subscale (Roininen et al., 1999). The agreement with these statements was indicated on a scale of 1–7, with 1 representing "Completely Disagree" and 7 representing "Completely Agree" (see Table 1).

To ensure sufficient variation, stratified random sampling was performed. The stratification criteria were: (1) each respondent likes apple juice, (2) there are roughly the same percentage of respondents in age category 20–42 and 43–65 years, and (3) there are roughly the same percentage of males and females. During the recruitment process only those that gave a positive answer to the question: "do you like apple juice?", were considered. For more details about the experimental design and consumer test procedures we refer to Olsen et al. (in press). For the purpose of this paper only the aspects relevant for illustrating the methodology proposed will be covered.

4. Results

All calculations in this paper were conducted in Unscrambler, Minitab and Excel without the need for software programming.

4.1. Yoghurt data

The full ANOVA model with all the relevant average and individual factors (according to model (1) above) gave the results presented in Table 2. These are the same as reported in Johansen et al. (2010). Note that since this is a reduced design, this model contains all possible interactions. Note also that due to confounding, only some of the interactions are possible to estimate. As can be seen, the interaction between sweetness and richness is significant at a 5% level. Three of the conjoint factors are highly significant. The degree of sweetness has the strongest effect, followed by a significant effect of richness and information about sugar while no effect was found for information about fat on liking. Both sweetness and richness increase liking while information about higher sugar content lowered it. The variance component for the interaction between sweetness and consumer is equal to 1.3 and the variance component for the random error is 2.2 while the rest are quite small in comparison. These results correspond well to the fact that sweetness was also dominating at the population level.

The residuals from the model using only the conjoint factors, all their interactions and the main effect for consumers were then computed and put into a matrix with the rows corresponding to consumers and the columns corresponding to the products (153×8). A PCA was then run on this matrix of raw residuals without any standardisation and the loading and score plots, shown in Fig. 1, were obtained. The explained variances for the two first components were 49% and 24% for the fitting and cross-validation (see e.g. Martens and Næs (1989)), respectively. The third component explains 11% of the variance giving about 60% explained variance after 3 components. This corresponds reasonably well to the relative importance of the systematic variance components as compared to the random error part. This indicates that one should not put too much emphasis on components beyond 3.

The first component is strongly related to the sweetness of the yoghurts tested. On the right side of the plot we therefore find people who prefer yoghurts with a high sweetness (product codes starting with 2) whereas those who appreciate a lower sweetness are positioned on the left side (codes starting with 1). The second component is related to richness: positive values of PC2 are related to low richness (yoghurts coded with 1 as second number) and negative values mean the opposite. The third component is, however, more difficult to interpret. No clear structure can be seen for any of the digits in the codes. We therefore concentrated on the segments obtained for the two first components.

Table 2
Results from ANOVA of the yoghurt data: *P*-values, averages and standard errors for fixed main effects and interaction effects (0.00 means a *P*-value ⩽0.01). LL refers to low level while HL refers to high level. No Bonferroni correction is made.

Fixed effect	Liking *P*	Mean (Std. Error)	
Main effects		LL	HL
Sweetness	0.00	4.683(0.060)	6.559(0.060)
Richness	0.01	5.482(0.060)	5.756(0.060)
InfoSugar	0.01	5.747(0.060)	5.495(0.060)
InfoFat	0.79	5.634(0.060)	5.608(0.060)

		LL First factor		HL First factor	
Interactions	Liking *P*	LL Second F	HL Second F	LL Second F	HL Second F
Sweetness*Richness	0.03	4.454(0.085)	4.912(0.085)	6.510(0.085)	6.608(0.085)
Sweetness*InfoSugar	0.15	4.748(0.085)	4.618(0.085)	6.745(0.085)	6.373(0.085)
Sweetness*InfoFat	0.82	4.686(0.085)	4.680(0.085)	6.582(0.085)	6.536(0.085)

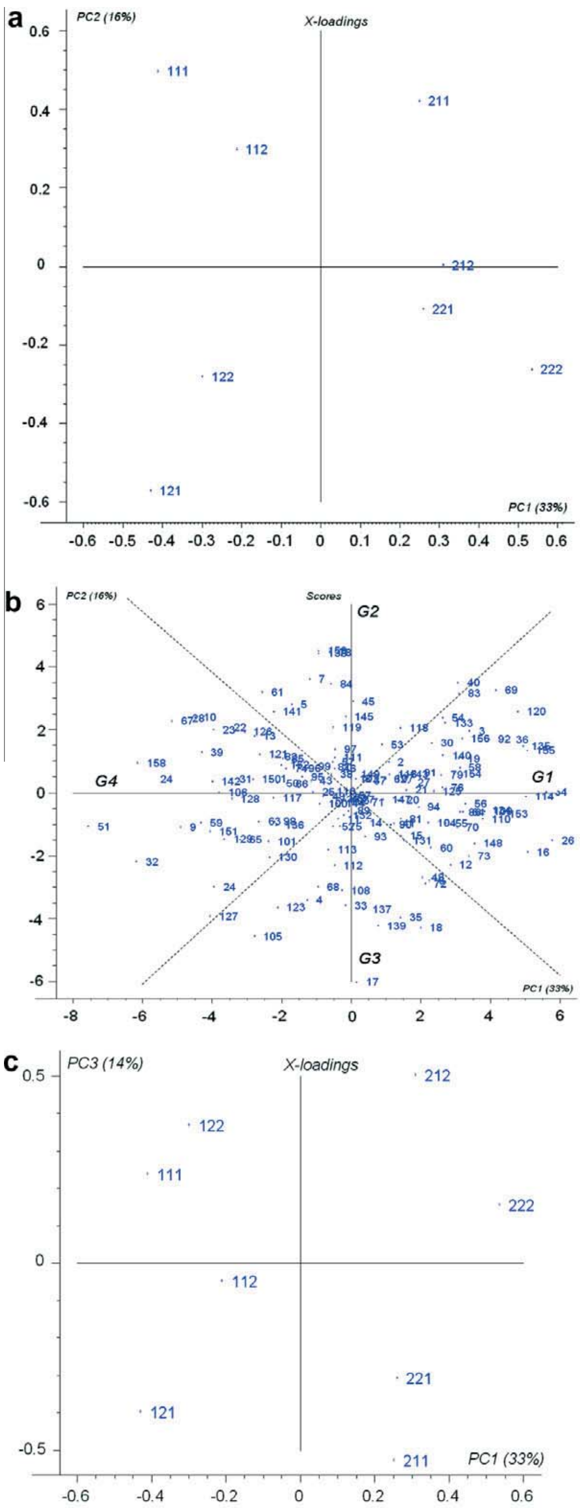

Fig. 1. Loadings (a) and scores (b) with cluster indication from the PCA of the double centred residuals of yoghurt data-set. In Figure (c) are presented the loadings for the first vs. the third component. The codes in the loading plot give a direct indication on sample composition in terms of sweetness (first number in the code), richness (second number in the code) and information about sugar content (third number in the code) representing their low level (1) or high level (2). No code is added for information about fat since this was found of minor interest in the ANOVA.

We emphasise, however, that if the third component is meaningful, it is also possible to use that in the segmentation exercise, both in combination with the other two components or separately. This emphasises the flexibility of the approach, namely that segments can be decided based on which aspects of the differences one is interested in studying. One should, however, always validate the segments using the plotting of the average values as illustrated below (Figs. 3). This is particularly important when there are many components and if the visual segmentation is based on a limited number of components. In such cases it is important to verify that the segments represent what is indicated in the PCA plots. If wanted one can support the segmentation by automatic clustering methods, but in situations like the one depicted here with no clear splitting of the consumer group, this may depend heavily on clustering method used. The third component will be considered in the second data set.

Although a very clear interpretation of the two axes is obtained here, for illustration we also used the method presented in Eq. (3). For both axes, the conclusions were identical to those obtained by

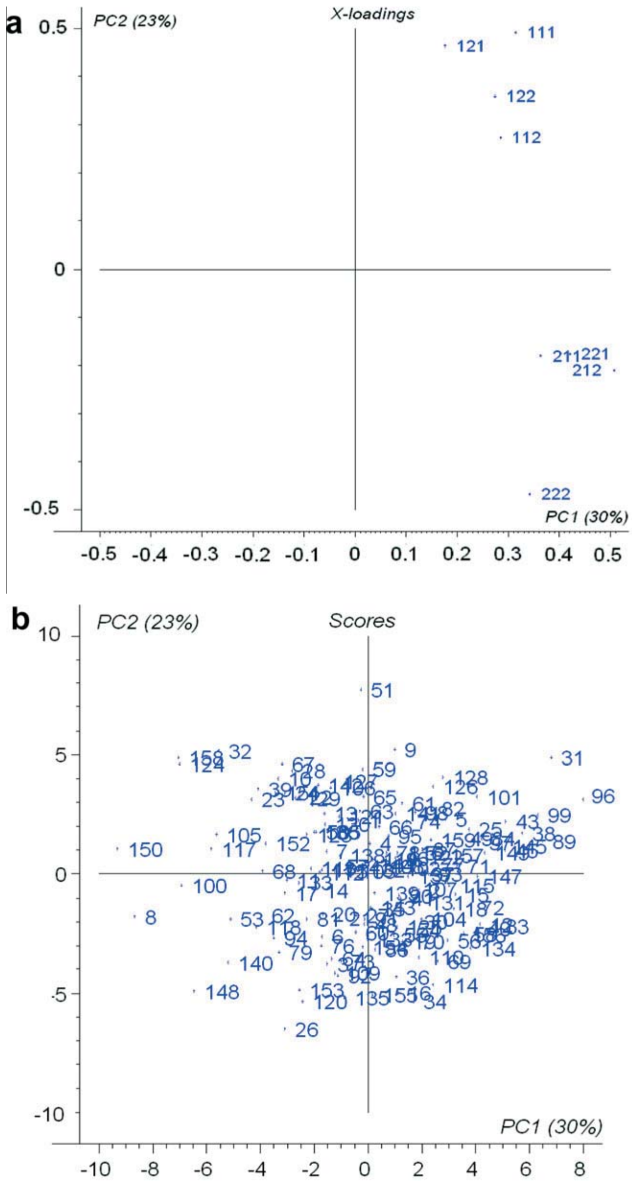

Fig. 2. Loadings (a) and scores (b) without the consumer effect for yoghurt data-set. The codes in the loading plot give a direct indication on sample composition in terms of sweetness (first number in the code), richness (second number in the code) and information about sugar content (third number in the code) representing their low level (1) or high level (2). The information about fat is omitted since this was found to have minor effect in the ANOVA.

visual inspection; the first axis is dominated by sweetness and the second by richness. When comparing mean squares (MS's) for the different factors the sweetness accounted for almost 100% for the first component and the same was the case for the richness and the second component.

In order to evaluate the importance of incorporating the consumer main effect when calculating the residuals, the model with just conjoint factor effects was fitted. We then used PCA on the residuals and obtained a plot with all the loadings being positive for the first component (Fig. 2). A natural interpretation of this is that without the consumer effect, the first component is mainly related to different (additive) use of the scale. We continue with the former which we think is generally the most relevant (see also preference mapping, McEwen, 1996).

The score plot was then segmented according to the interpretation above, namely according to both the sweetness and richness axes (Fig. 1b). Note that this is a natural choice since it has a clear interpretation, but that it is only one of a number of possibilities for segmentation. Therefore, the actual segmentation used for illustration here is only an illustration and it can be done according to what aspect of the data that one is interested in highlighting. The confidence intervals, obtained by standard methodology for confidence intervals of the mean (coefficient = 0.95), for the different effects and different groups are given in Fig. 3. The groups G1 ($n = 52$) and G4 ($n = 51$) are clearly opposite to each other when concerning liking of sweetness and groups G2 ($n = 25$) and G3 ($n = 25$) are opposite when concerning liking of richness. There also seems to be a clear difference between group G1 and G4 when

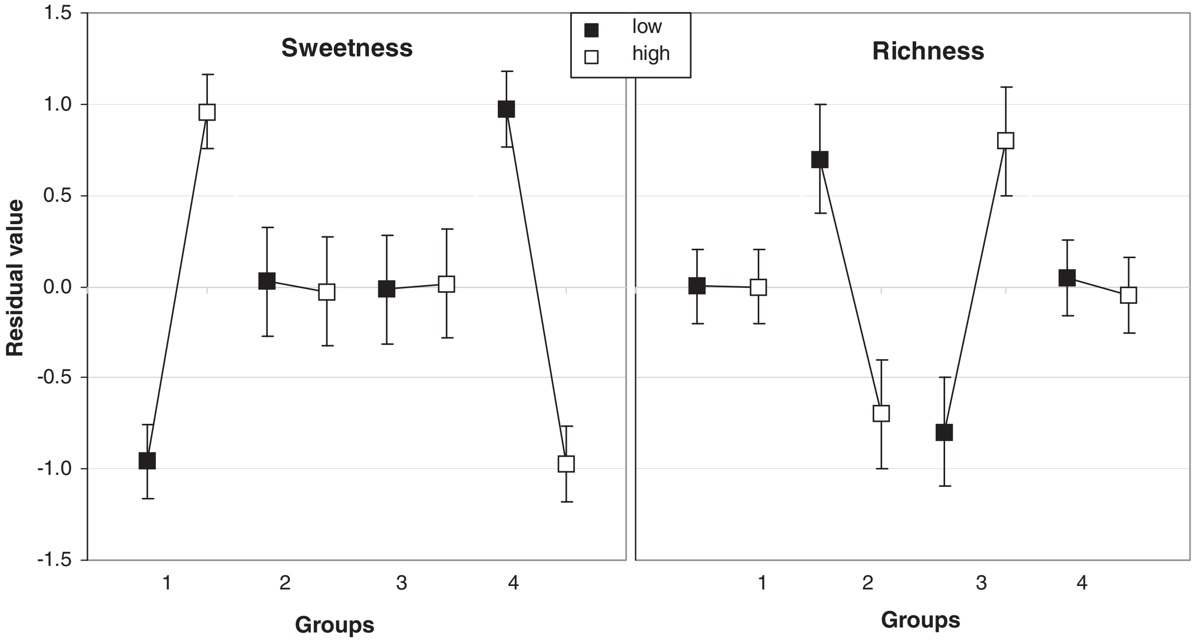

Fig. 3a. 95% confidence intervals of residuals for sweetness and richness in the four groups extracted from yoghurt data-set.

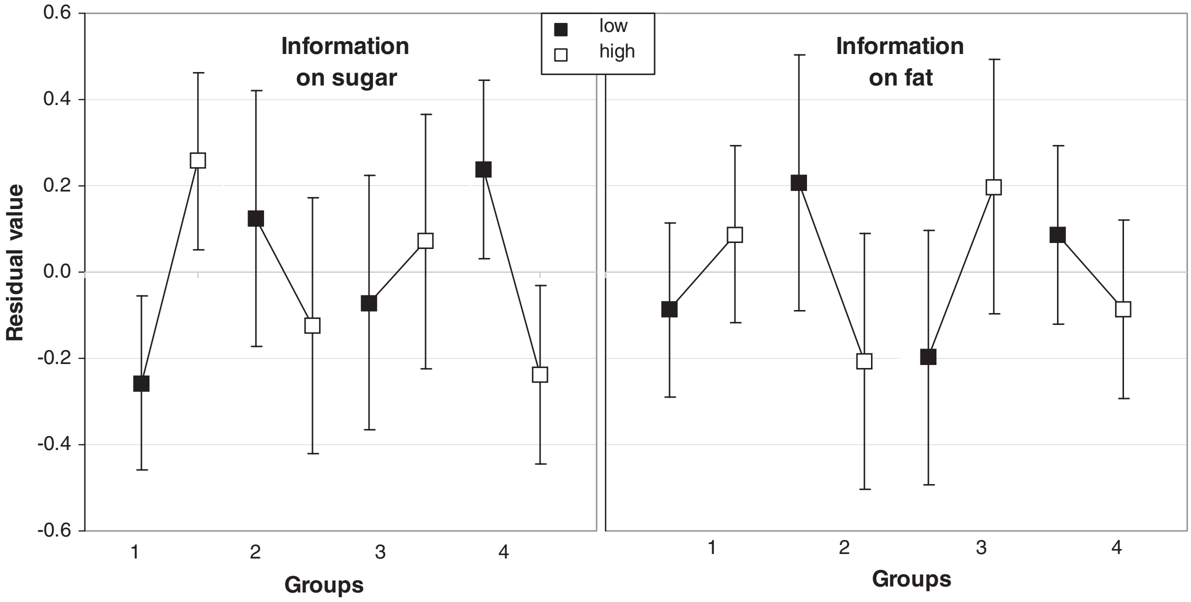

Fig. 3b. 95% confidence intervals of residuals for information about sugar and fat content in the four groups extracted from yoghurt data-set.

concerning information about sugar content, going in the same direction as the sweetness itself (see Fig. 3). An interesting observation is that although the information about sugar has a negative effect (although not very strong) in the population, it seems here that when considering the segments, the sweetness and information about sugar go in "the same direction", i.e. if people like sweet yoghurt they also react positively to the information about sugar. For groups G2 and G3, although the information about fat content is not significant, a similar tendency for richness and information about fat content (of going in the same direction) can be observed. As can be seen, the same effects that are important in the population are also important here and the magnitudes of the differences between the groups are quite large as compared to the population effects.

Next we tried to characterize the four groups in terms of collected demographic and attitude data. To do this, PLS-DA was used on the consumer information data after subtraction of the mean for each consumer for the attitude data. Non-centred consumer attributes were likewise tested and only small differences were observed. Then, all the variables were standardized before using

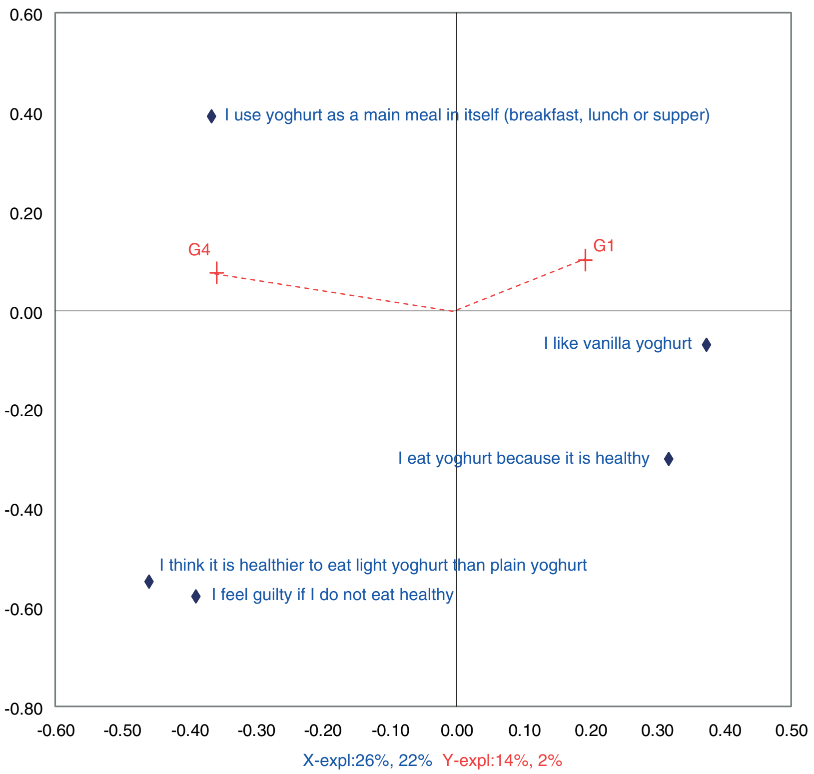

Fig. 4. PLS-DA plot for groups G1 and G4 of yoghurt data-set.

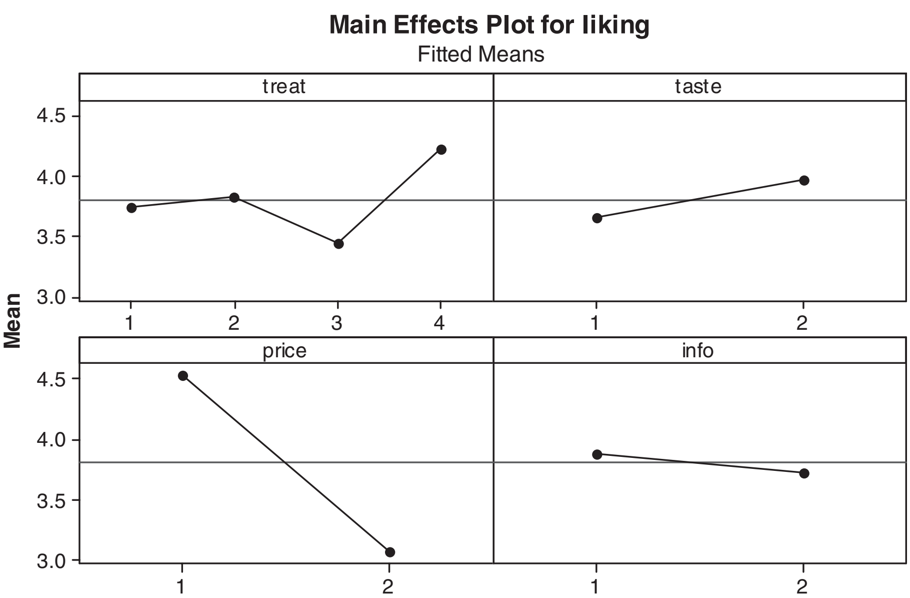

Fig. 5. Main effects plot for the 3 conjoint factors and information level of apple juice data-set. All conjoint factors are significant. The standard errors for the treatment effects are 0.10, for the taste they are 0.09, for price 0.09 and for info 0.10.

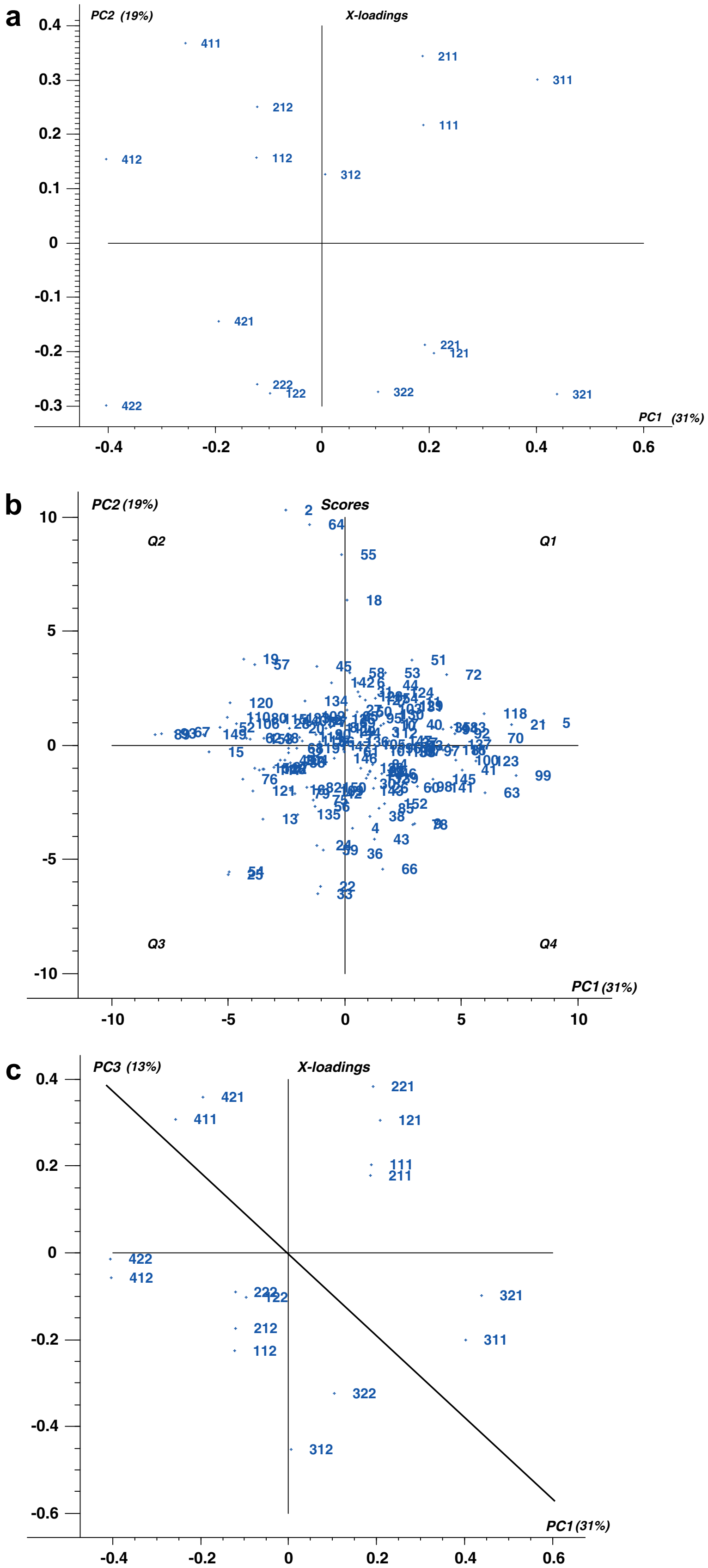

Fig. 6. Loadings (a) and scores (b) plot from the PCA of the double centred residuals of apple juice data-set (method 1). The first digit in the code (loadings plot) corresponds to treatment (1–4), the second to taste (1, 2-standard and premium) and the third to price (1,2, low and high). Figure (c) shows the loadings for the first vs. the third axis. The superimposed line indicates the split between high and low price.

them in the model. Here, we concentrate on the comparison between group G1 which consists of consumer who prefer the sweeter products but also products with an indication of high level of sugar, and G4 which consists of consumers representing exactly the opposite acceptance pattern. The same type of comparison can be made for the richness effect.

First we considered the plot with all attitude variables involved. Only five of the variables showed a significant relation to the groups according to the jack-knife method. Subsequently, a new analysis with only the significant variables was conducted. The positioning and interpretation of the five variables was similar in the full and reduced analysis. The results are presented in Fig. 4 for the reduced model. Consumers in G1 are people who like vanilla yoghurt and eat it because they think it is healthy. In group G4 the consumers think that it is healthier to eat light yoghurt instead of the plain (full-fat and sugar containing) one. They declared to feel guilty if they do not eat healthy and they use yoghurt as a main meal in itself. These results make sense in terms of the interpretation of the acceptance pattern given above; those who like the less sweet yoghurts and information about a low sugar content are those with a more positive attitude towards the healthy aspects. The explained cross-validated Y-variance (for the dummy variable) for the model with two factors was 11% (10% after one component, note that this can be overoptimistic when only significant variables

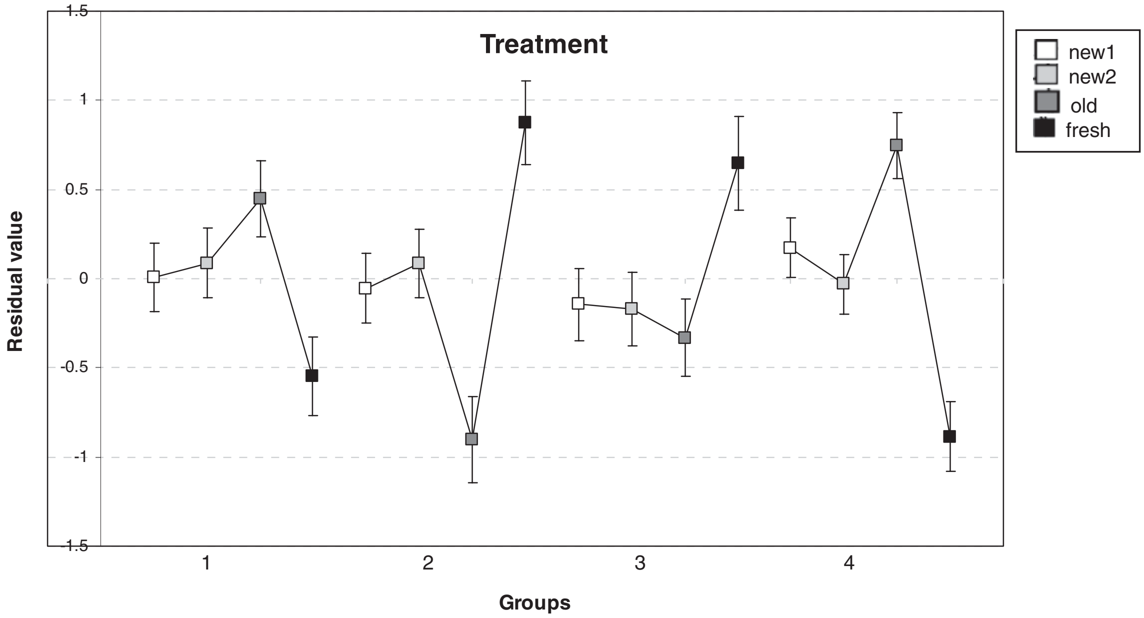

Fig. 7a. Residual confidence intervals for each treatment in each group extracted from apple juice data-set.

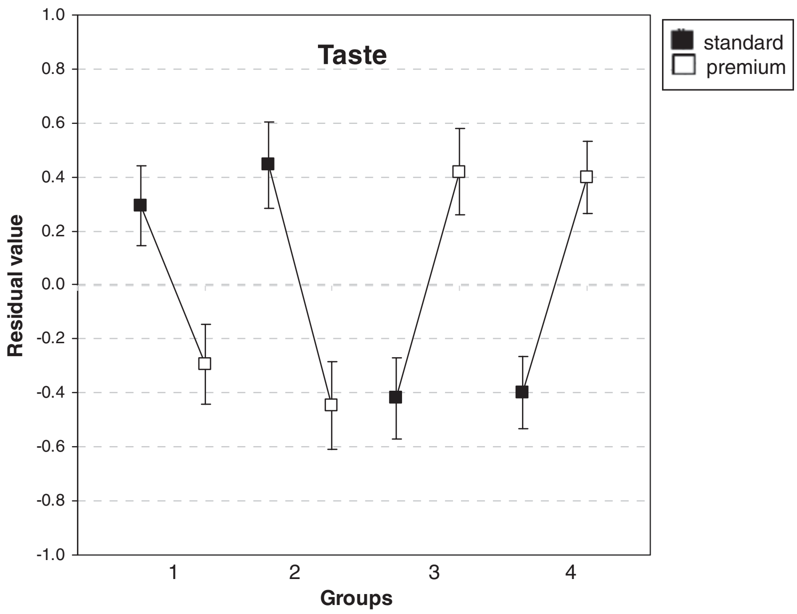

Fig. 7b. Residual confidence intervals for the two levels of taste in each group extracted from apple juice data-set.

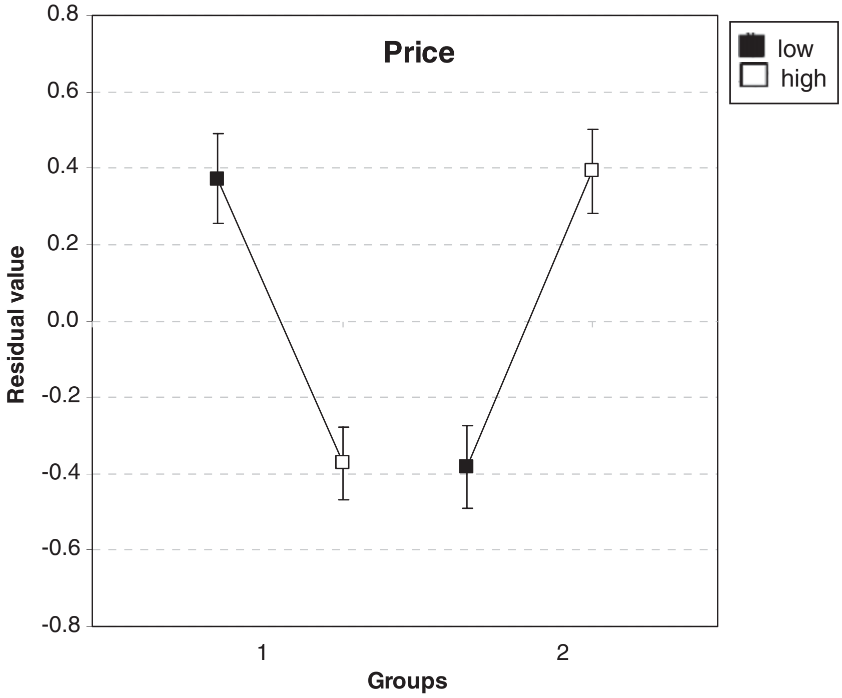

Fig. 7c. Confidence intervals obtained from the segmentation based on components 1 and 3 in Fig. 6.

are used, see above). The explained validation variances for the *X*-data (consumer characteristics) were 5% and 10% for 1 and 2 components, respectively.

4.2. Apple juice data

4.2.1. Results from the approach proposed

The first ANOVA model takes into consideration all the main effects, two-factor and three-factor interactions. The random consumer factor is incorporated as nested under the information factor. Random interactions between the consumer effect and the conjoint factors and their interactions are also incorporated as nested. The results for the four main effects are presented in Fig. 5. All three conjoint factors were highly significant while the information factor was not. For the conjoint factors, the only interaction that was slightly significant was the one between treatment and price. The variance components for the random effects correspond well to the average effects in the sense that the dominating contributions were related to the interactions between consumer and the three conjoint factors, with only a small contribution from the three-factor interactions. The random error variance was comparable to the variance components of the interactions between consumer and the conjoint factors.

Then, we used the saturated conjoint model (main effects and all interactions up to fourth level) and with the main effect for consumer. Note that the difference from above is that extra interaction terms are added. For the standard ANOVA with focus on significance, these types of higher order interactions are usually of no interest, but for the purpose of obtaining a saturated model, as advocated above, this is necessary. From this ANOVA we computed the (double centred) residuals, and put them into a matrix with the consumers as rows and the products as columns (154×16). A PCA was run and loading and score plots were interpreted (Fig. 6). The two first principal components explain 51% of the total variability (41% cross-validated, full cross-validation, see e.g. Martens and Næs (1989)). The first component primarily relates to the treatment factor and the second component almost exclusively to the taste factor. Negative loading values along the first component correspond to fresh juices and products with high price (relative to the others) whereas positive values for PC1 correspond to old and new treatments and low price. The second component separates between standard taste products (upper part of the plot) and premium taste ones. Again one gets information about which effects are the most important at an individual level and again the magnitudes of the differences are quite large. The third component is essentially a price component related component, but has also a relation to products (4 is higher up than 3 with 1 and 2 in the middle).

In order to illustrate the method indicated in Eq. (3), the ANOVA was used both for the first and the second principal component (loadings) using all the three conjoint design variables. For the first component, the relative sizes of the mean squares were 38%, 1% and 61% for treatment, taste and price, respectively. For the second component the corresponding values were 1%, 95% and 4%. As can be seen, this corresponds well to results obtained by visual inspection. This method can also be very useful when the interpretation is less obvious than here and when the number of factors and levels are large.

For illustrating the differences in acceptance pattern among consumers we decided to split the consumer groups into four segments according to which quadrant they belong to (Q1: 41 consumers, Q2: 40 consumers, Q3: 34 consumers, Q4: 39 consumers). The four segments can be interpreted as indicated by the interpretation of the two PCA axes. For instance, the third quadrant (Q3, lower left) is characterised by consumers with higher preference (than the average) for more expensive products and fresh juices. Segment Q1 on the other hand consists of consumers who prefer standard taste products with low price. The segmentation thus makes sense in terms of interpretation, but other segments could likewise have been chosen. This concrete segmentation is only selected as an example, but as stated above, it makes sense as a clear separation of consumers according to the interpretation of the plots. As an illustration we also did a second segmentation based on the components 1 and 3, i.e. a segmentation based on price.

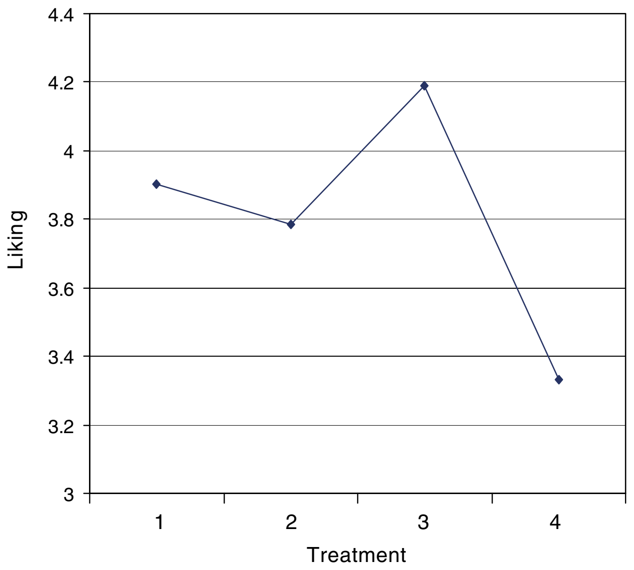

Fig. 8. The average results for segment 4 added to the average effects in Fig. 5 for the 4 treatments. If the exact levels of the liking estimates are important, not only the relative differences, the average of the main effects of the actual consumers in the segments can also be added (see formula (2)). Since the standard deviations for the four treatments are slightly different, the standard deviations (standard errors) for the averages in this figure are slightly different. Here they vary between 0.13 and 0.14.

The straight line indicates the splitting of the products with high (lower part) and low price.

The confidence interval plots (coefficient = 0.95) of the residuals, based on the segmentation from the first and second component, are presented in Fig. 7a for the treatment and in Fig. 7b for the taste characteristics. As can be seen, these results correspond to and highlight the differences in the segments in their acceptance pattern. Quadrants Q1 and Q4 have a similar trend in relation of the treatment factor: juices with old treatment have a higher preference as compared to the average consumer than what is the case for the fresh products, and new treatment juices are in an intermediate position. The Q2 quadrant shows an opposite pattern for old treatment vs. fresh untreated products. The interval plot related to the taste factor is in addition interesting: Consumers which belong to group Q1 and Q2 prefer standard taste while the favourite taste for Q3 and Q4 is evidently the premium one, with the strongest acceptance in the last group.

The confidence intervals for the segmentation based on the first and third component are presented are Fig. 7c. As can be see, the tendency is strong; the differences in perception of price are totally different in the two segments.

All these results show that even though there is a general tendency as reported by the main population effects, there are large individual differences, some of the consumers even rate the products in opposite order as compared to the average. As can be seen, by adding the average values for group 4 in Fig. 7 to the average values in Fig. 5 we obtain a pattern which is quite different from the total average (Fig. 8).

The next step is to relate the four groups to external variables. We concentrated on the centred external consumer characteristics since we think this in most cases is most relevant (removes additive scaling differences, see also for the other example). The external characteristics were used as *X*-variables and the four groups as *Y*-variables. This was done by establishing two dependent variables, one defining values larger/smaller than 0 for the first component and the other one defining larger/smaller than 0 for the second component. The loadings are presented in Fig. 9. In this case, the explained variances were 57% for the *X* and 4% for the *Y*. For cross-validation, the *X*-variance for two components was 35% and 5% and for the *Y*-data only the first component was significant according to cross-validation. As can be seen, the

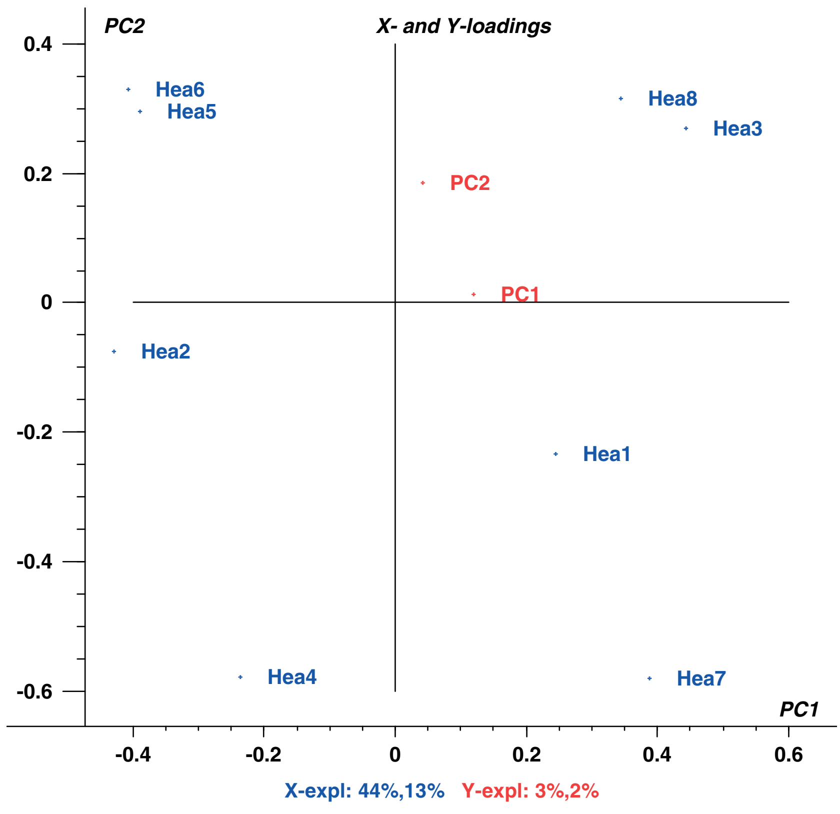

Fig. 9. Loadings plot for PLS-2 for the apple juice data. The PCA and PC2 illustrate the direction of the segmentation variables as described in the text. The two axes obtained correspond very well to the PCA axis found in Fig. 6. The Hea1, Hea2, etc. variables correspond to the statements in Table 1.

positive and negative health attributes are represented on different sides with the positive ones going in the direction of the fresh juices, which could be expected.

As can be seen, the health attributes are split in two along the first component. The health positive statements are to the left and the health negative statements on the right along the first principal component. Comparing with the results above the health positive attributes correspond to those consumers that prefer the fresh juices while the health negative attributes correspond to those who prefer the other juices which makes sense and supports the validity of the clusters. It should also be stressed here that the fresh juice direction is also related to price as was described above.

4.2.2. Comparison with PLS on raw data

As a comparison we did a PLS analysis as described in Section 2.4. In this case we subtracted the mean for each consumer for the liking values (as was essentially done also for the residuals above). The loadings plot is shown in Fig. 10. The health variables split the same way as for the residuals plot along the first axis, but along the second the situation is a bit different. In this case, the second dimension is essentially a dimension contrasting Health 8 to Health 1 with the others in a intermediate position. It seems that there is a tendency that the products with low price lie more to the right than the rest, which means that there seems to be relation between the reverse variables 1, 3, 7 and 8 and low price and between 2, 4, 5 and 6 and high price. There is also a clear tendency that the pasteurised products go in the same direction. For the other products (first digit in the symbol), the differences are more unclear.

The fact that the health negative attributes are linked to pasteurised juices and to a certain extent also to low price and the other juices more to the health positive attributes corresponds well to the results for the residual approach above. The second dimension is, however, more difficult to understand in both cases.

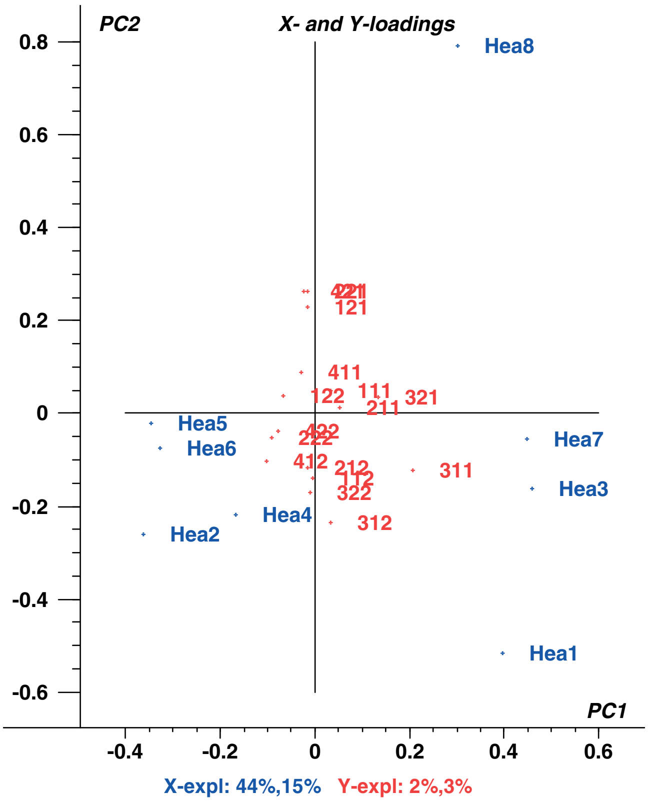

Fig. 10. *X*- and *Y*-loadings for the PLS-2 analysis of the liking values vs. consumer attributes related to health (see Table 1).

For the residual approach the second PCA dimension is clearly related to taste (second digit) which indicates that in this sense the residual approach is more able to highlight individual differences in liking than the PLS approach. This may give an advantage for understanding the individual differences in liking as was illustrated in Fig. 6 and Fig. 7), but when comes to understanding the relation between liking and the consumer characteristics, the differences between the two approaches did not indicate any strong difference for the concrete characteristics considered. The PLS approach does not provide any direct information about the population average effects and their significance as the ANOVA/residual approach discussed in this paper.

5. Discussion

5.1. Methodological aspects

The present approach is based on a joint fitting of all consumer liking data to the conjoint factors and is in this sense identical to the standard approach when concerning estimates of population utilities and part worths. The residuals are combined in a matrix and analysed by PCA for the purpose of segmentation. If sensible consumer segments are found they can later be related to consumer attributes by PLS regression which can easily handle a larger number of possibly collinear variables, which is difficult when consumer characteristics are incorporated directly in the ANOVA approach. Variable selection can be done using the jack-knife method, if the number of variables is very large. The method is based only on simple and well established tools such as ANOVA, PCA and PLS regression and can be conducted in most statistical packages without extensive programming. The method is thus flexible, simple and transparent and it can be used for all different types of external consumer attributes.

It should be stressed that this part of our method bears some similarity with the approach based on using ANOVA for each consumer separately with subsequent analysis of the individual effects for the conjoint factors in a second step. If these individual effects are collected in a matrix with consumers as rows as was suggested in Næs et al. (2010a and 2010b) and thereafter related to consumer characteristics with the use of PLS, this is quite similar to what is proposed here, the only differences being the structure of the *Y*-data. In this sense, the approach presented here can be considered as an approach that combines the population oriented approach and the individual differences ANOVA's into one single approach.

The way of constructing the residual matrix proposed here gives a double centred matrix with the property that it highlights differences between consumers in their relative position as compared to the average consumer values. This is particularly useful for highlighting differences in preference pattern among the consumers. In this sense, the two first PCA components represent the best possible splitting of consumers with respect to these relative differences.

The present approach splits the analysis of the acceptance pattern from the analysis of the consumer characteristics. In other words, all segmentation is here taking place based on differences in acceptance pattern. This is in our opinion a more transparent approach as compared to some of the methods which combine the two into one analysis (see e.g. L-PLS regression, Martens et al., 2005). In these other approaches it is in our point of view still not fully clarified how much the different aspects contribute with and in which way one should interpret the results.

The segmentation and interpretation of segments is graphically oriented. This is useful since one can more easily determine segments according to prior knowledge and focus of the study. In addition, it is very seldom to find clearly separated segments in consumer science, indicating that segmentation will always have a strong subjective element in it. This often makes a visual approach more suitable than an automatic approach. If wanted one can, however, support this by more automatic clustering procedures accompanied by visual inspection of the clusters afterwards. The problem, however, is that often the suggested segments may be dependent on the method used and interpretation may become difficult. The mentioned flexibility is illustrated by the fact that different strategies are used for the two examples. In one of the examples, the four quadrants are used as segments, while in the other one the segments are obtained differently.

The relation between segments and external consumer attributes were calculated in both examples. In both cases, the results were reasonable and as expected. This supports the validity of the clusters. As could be seen, for factor with two levels the values within each group have identical absolute values. This comes from the fact that the design is balanced and that the residuals sum to 0 for each consumer.

In all cases, it was possible to do the calculations using combinations of the standard methods without the need to programming skills.

5.2. Empirical results

For the yoghurt data, splitting the consumers in four groups revealed very different acceptance patterns. Although, sweetness on average was shown to have a large impact on consumer acceptance of calorie-reduced yoghurt, the results showed that this was only true for two of the consumer groups (G1 and G4).

The results from the apple juice data indicate that one can obtain a more detailed picture when we split the consumers into segments. The general tendency as reported by the main population effect is that Norwegian consumers perceive novel treated juice with 6 weeks shelf life to be a better choice than conventionally treated juice with 1 year shelf life if the price and taste is right. When splitting the population into four segments we find that two of the segments perceive fresh juice to be the best alternative, while the other two groups perceive conventionally treated juice to be the preferred alternative (see Fig. 7a). By splitting the population into segments we can still see that the new treatment juices are perceived as a good second and third choice. These observations are in line with the main effect and support the general tendency from the total population that these novel juices are rated in between fresh and conventionally treated apple juice. However, the picture that fresh juice is always perceived as the best alternative is no longer supported when we look at the segments. According to Fig. 7b) two of the groups prefer premium juice, while the other two prefer standard taste.

6. Conclusion

This paper presents and discusses a way of analysing individual differences in conjoint analysis based on ANOVA. The method provides both population average estimates of the utilities as well as estimates as a graphical overview of individual differences. The method is based on only well established methods such as ANOVA, PCA and PLS and can be run in most statistical software packages without advanced programming. The method is graphically oriented and can also be used for segmentation. The advantage here is that the segmentation can be done both based on visual interpretations of the results and by the use of more automatic methods if wanted. The consumer segments can then be related to external consumer characteristics using for instance regular PLS discriminant analysis. The method is tested out on two data sets previously treated by other methods. It is shown that when individual differences are analysed by the present method, interesting results regarding individual differences in response pattern were detected. The clusters were validated by external consumer attributes.

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Paper II

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Combining extrinsic and intrinsic information in consumer acceptance studies

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ABSTRACT

This paper proposes a methodology for combining extrinsic and intrinsic attributes in consumer testing of food products. The paper attempts to focalize on the main sensory drivers of liking or choice probability and their interaction with additional information, and to investigate effects related to the population as well as how consumers differ in their assessments. Two different data analysis approaches are considered and compared on choice probability data from a consumer study of orange juice. One of the methods is based on mixed model ANOVA of individual differences, the other approach is based on fuzzy clustering related to regression residuals. The main results show that extrinsic consumer attributes are easily and efficiently related to the sensory properties of products, allowing for interactions. The methodology estimates population or segment means and gives an overview of individual differences in choice intent or liking.

1. Introduction

Both intrinsic sensory attributes and extrinsic factors related to all other aspects of the product and its presentation are important for consumer choice probability or liking of food products. For instance, when buying yoghurt, the sensory properties of the yoghurt, information about sugar and fat content (Johansen, Næs, Øyaas, & Hersleth, 2010b) as well as the packaging are all important for the choice. In product development it is therefore useful to investigate consumers' acceptance in light of all these aspects. Very often the two types of attributes are investigated in independent tests, but in some cases this may be insufficient. If for instance the difference in consumer choice probability between two products depends on information about health benefits, this type of information is not possible to get without using a test where both aspects are involved. This facet is particularly important to take into account in research when the purpose is to understand patterns in human perception and liking or choice probability, but it may also be highly relevant in concrete industrial product development situations. In such cases it is therefore crucial to have techniques available that can be used to investigate both intrinsic and extrinsic attributes simultaneously.

A number of studies have been conducted where consumers are given food samples together with additional information (Johansen et al., 2010b; Stefani, Romano, & Cavicchi, 2006; Urala & Lähteenmäki, 2006; Visschers & Siegrist, 2009), but most of these studies consider a number of fixed samples and end up with drawing conclusions more related to differences between the actual products than to the important sensory drivers of liking or choice probability (Enneking, Neumann, & Henneberg, 2007; Helgesen, Solheim, & Næs, 1997). In such cases, one typically uses standard factorial designs and Analysis of Variance (ANOVA) treating each product as a separate level of one of the experimental factors. This is an important methodology which can give a lot of insight, but its main drawback is that there is no or at least rather limited focus on the effects of the whole profile of sensory attributes of the products and how it influences consumer preferences. In other words, limited information is obtained about what the main drivers of liking or choice probability are and also about how these interact with the extrinsic attributes. This type of insight may be of crucial value when optimising product properties.

A methodology for solving this type of problem was proposed in Johansen et al. (2010b). This approach is based on first analysing a number of relevant samples for testing with the use of sensory analysis. This "large" number of samples may be obtained by for instance experimental design as done in Johansen et al. (2010b), but it may also be obtained by selection from a production process or from a store as long as the samples are relevant. This number, which may typically vary around 10, may, however, be too large for consumer testing in combination with other attributes. Therefore a selection strategy was proposed based on the scores plot from the Principal Component Analysis (PCA) of the sensory data. More specifically, the samples were selected to span a rectangular shape in the principal components plot, with the rectangular axes

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considered as meta-attributes with an interpretation given by the loadings. These meta-attributes were then used as regular attributes when combined with the extrinsic factors in a factorial design (or fractional factorial). The samples representing the corners in the rectangle were thus the samples used in the study in combination with the extrinsic attributes. Analysis was done with regular factorial ANOVA treating both the sensory meta- attributes and the extrinsic attributes as orthogonal factors with two levels each. The method is useful but considers only corners of a rectangle in the scores plot and therefore only linear models can be used. In some cases one would rather like to have information from the whole sensory space for the purpose of being able to use others than the linear models, for instance ideal point models (Borg & Groenen, 2005; MacKay, 2001; Næs & Risvik, 1996), and also for better model adequacy checking. Such ideal point models are typically quadratic polynomial models in the principal components of the sensory data, with the ability to identify both negative and positive peaks in the liking pattern.

The main challenges related to the design of such studies are to select the best possible subset of the food products to be tested and to combine them with extrinsic attributes in a simple way, preferably using standard well known methods. From an analysis point of view the main challenge consists of combining the large set of collinear sensory attributes with the extrinsic attributes, allowing for interactions and non-linearities, in particular when the number of samples is limited as it usually will have to be in consumer testing of real products.

It is quite obvious that for all this to happen one will have to accept some type of incompleteness in the design, but the question is how much one can allow and what consequences this may have. The most natural thing to do is probably to serve to different consumers different products in such a way that together the products cover the whole sensory space. Another aspect which is quite obvious is than when analysing the data one will need some type of data reduction, by for instance PCA, of the sensory profile.

In this paper we propose a new strategy to handle these problems. The procedure is relatively simple and based on standard well established principles from experimental design, multivariate analysis and ANOVA. The limitations of the method will also be discussed, with a special emphasis on how much can be concluded about individual differences in choice probability. The method is based on using different products for different consumer groups, but it ensures that the whole sensory space is covered as well as possible. Note also that, since the different consumers are allowed to test different products, the amount of material needed for each of the products is less than if all consumers tested all of them. This may for instance be an advantage in studies involving products that for some reason are difficult to provide in larger quantity. Note that when no interactions between intrinsic and extrinsic attributes are present, one can use standard conjoint and preference mapping methods for analysing the two separately.

For the analysis, two different approaches are appropriate and will be tested. The first is to use ANOVA with a fixed effects contribution representing the average population effects and a random effect contribution accounting for individual consumer differences (Johnson & Wichern, 2007; Næs, Brockhoff, & Tomic, 2010; Næs, Lengard, Johansen, & Hersleth, 2010). The method focuses on the average population effects of both the intrinsic and extrinsic attributes, but we will also propose an analysis of the individual differences along the same lines as proposed in Endrizzi, Menichelli, Johansen, Olsen, and Næs (2011). Special emphasis will be given to the limitations and possibilities at this point. The other approach is based on fuzzy clustering using regression residuals, as discussed in for instance Næs, Kubberød, and Sivertsen (2001), Johansen, Hersleth, and Næs (2010a) and Wedel and Steenkamp (1989),Wedel and Steenkamp (1991). The method has the advantage, since it is based on residuals, that it can be used also when the different consumers have tested different products, as they do in this study. The method is designed for finding segments of consumers with a similar response to the intrinsic and extrinsic variables. In this sense the approach is an extension of the method in Johansen et al. (2010a) which only considered fuzzy C-means (FCM) and intrinsic effects. It will be concluded that the method as it stands now is best suited for estimating population or segment means, but also suitable for giving a rough overview of individual liking differences.

The methodology is tested out on a data set from a consumer study of orange juice. A total of ten different juices were tested in combination with information about price and production process. The aim was to investigate which of the intrinsic and extrinsic properties are the most important for consumer choice probability of the product.

2. Methodology

For the purpose of this paper the following points will be important:

- The products selected for the test should cover the sensory space in such a way that both linear and non-linear models for the sensory attributes can be used, at least at a population or average level.
- It should be possible to combine products and extrinsic factors in the study, preferably using rather standard experimental design procedures.
- It should be possible to estimate extrinsic effects, intrinsic effects and interactions between them, again at least at population level.
- Analysis should be simple and reveal both population structure and individual differences among the assessors, as far as the data allows.

2.1. Design

The design strategy proposed here is based on the following steps:

- Find a large set (typically 8–15) of relevant products for the problem of interest. Analyse all of them by standard sensory profiling analysis.
- From the PCA scores plot of these data, select a few products (3–5) to be tested by each consumer in such a way that they span the space as well and as evenly as possible. One can use different products for all the different consumers, or split into subgroups and give each subgroup a different product set. When considering the consumer group as a whole, the entire scores space should be covered as evenly as possible.
- For each consumer, combine each product with the same factorial or fractional factorial design in the extrinsic attributes, considered as categorical variables.

Note that we here implicitly assume that the PCA scores space covers the important variability for consumer choice probability for all the products, which is similar to what is done in regular preference mapping. If wanted, one can use more than two dimensions, but this is more challenging since more products have to be tested by each consumer in order to get a reliable model.

The method to be tested below is based on a full factorial design in the extrinsic attributes, but it can in the same way be used also for fractional factorial designs. The important point here is that the same design is used for all consumers. Questions related to possibly relaxing on this assumption will be treated in the discussion below.

2.2. Analysis

Here we will consider two different approaches to analysis of the data.

2.2.1. Mixed model ANOVA

The mixed model ANOVA allows the total variance to be partitioned into components related to the different sources of variation. The approach used here is based on two parts, one part representing all relevant main effects and interactions as fixed average/population effects, and a second random part representing the individual consumer effects and their interactions with the fixed effects (Næs, Brockhoff, et al., 2010; Næs et al., 2001. It is clear from the way the design is set up that for the fixed part of the model one has large flexibility with respect to how to incorporate both the extrinsic attributes as well as the intrinsic sensory attributes, in particular when the sensory properties are first projected down to the most important principal components. One may for instance decide quite freely what type of model is assumed for the intrinsic attributes (for instance polynomial models) and how these relate to the extrinsic factors (interactions). For the individual differences part, however, one will have to attain to restrictions given by the design and the products used for the individual consumers. If for instance only three or four products are given to each consumer, one will not be able to incorporate quadratic and interaction effects in the consumer part of the model, but will have to stick to a linear model.

As an example of the type of model to be used here, consider a situation with one only extrinsic categorical factor (A) at two levels and two intrinsic attributes represented by continuous principal components x_1 and x_2 of the sensory data. This is an extension of ANOVA, namely Analysis of Covariance (ANCOVA): we include in the model not only categorical variables, but also continuous variables for predicting the response. The index i in the model below corresponds to the levels of the extrinsic factor, the index k to the product for which the two intrinsic factors are measured and n represents consumer. Note that not all combinations of n and k are present since product k is not tested by all consumers.

A possible model for such a situation can be written as

$$\begin{aligned} y_{ikn} &= \text{Population effects} + \text{Individual effects} + \text{noise} \\ &= \mu + \alpha_i + \beta_1 x_{1k} + \beta_2 x_{2k} + \beta_{12} x_{1k} x_{2k} + \beta_{i1} x_{1k} + \beta_{i2} x_{2k} + \beta_{i12} x_{1k} x_{2k} \\ &\quad + C_n + \alpha C_{in} + \beta_{n1} x_{1k} + \beta_{n2} x_{2k} + e_{ikn} \end{aligned} \tag{1}$$

where y_{ikn} corresponds to the iknth observation, μ is a general mean, α_i considers the main effects for the factor A (the average effects of the ith level of the extrinsic factor), C is the consumer effect and the βx's represent the various contributions from the two intrinsic variables.

The effects in the second line are the population effects and the effects in the last line are the individual contributions plus noise. As can be seen, in this particular model the population effects of the intrinsic factors are allowed to interact with the extrinsic factor: there is a basic β-contribution without an i index in it and also a contribution with an i index for the β coefficients. In addition, the two intrinsic factors are allowed to interact, as a product x_1x_2 is incorporated. On the individual level, the consumer effect, its interaction with the extrinsic factor and its interactions with intrinsic attributes (sensory attributes) are incorporated, as n is present in the β coefficients.

The elements in the last line are random. In this case only linear effects are incorporated, but more elaborate models can be used if the design allows. If only three products are tested by the same consumer, as is the case in the example below, only linear effects for the individual consumers' part of the model are possible. Note, however, that this does not influence the allowed model complexity at population level. Below we will investigate the sensitivity of the results for the population effects with respect to the complexity of the model used for individual differences. There is some evidence from Olsen et al. (2011) that the effect of the complexity of the random models is moderate. Since three-way interactions and higher are generally often small, a simplified random part may also seem natural from this perspective. In addition the fact that the random error itself and the additive consumer effect are often large as compared to the other systematic consumer effects is an argument in the same direction (see example below). If this aspect is a major concern, the alternative may be to use FCM as discussed below, where the consumer population is split into as homogeneous groups as possible and analysed separately without an individual random component.

The results from the model in equation (1) will typically be given in terms of significance of the effects, plots of the effects and their interactions and also contour plots over the principal component space to visualise the average liking pattern. Also the variance components for the individual differences are important in order to obtain insight into their size and importance.

The analysis method used in this paper is based on fixing a reference value for each of the extrinsic effects. The interpretation of the different effects is therefore relative to this reference. This means for instance that the effect of x_1 in the population, which is represented by the β values without an index, is related to the effect of x_1 for the reference value of the categorical extrinsic variable. If the effect of x_1 depends on the level of the categorical variable, this will be visible in the interactions between x_1 and the extrinsic factor, i.e. in the β-coefficient with an i index. The significance of all factors, including the main effects, will be defined as the significance of the regression coefficients of the variables relative to the reference level.

For further analysis of the individual contributions one can consider residuals from the ANOVA models as discussed in Endrizzi et al. (2011). In the residual matrix the consumers represent the rows and the factor combinations the columns. In this case, however, several of the columns in the residual matrix will contain information about different food products and it is not obvious how to handle this. An alternative which, however, only concentrates on the individual differences in sensory choice probability is to use residuals with respect to the model that accounts for both the fixed effects and the individual part that contains information about the extrinsic attributes. Therefore for the model above both C and αC are here incorporated when fitting and computing residuals, and only βx_1 and βx_2 are kept out. Since each product is repeated more than once, we propose to take the residuals' average over the extrinsic variables for each of the consumers. This gives a matrix with the consumers as rows and the number of food products as columns. For each product (columns) there will be many missing values since different consumers tested different product sets. If this matrix is transposed, it can easily be analysed by external preference mapping using Principal Component Regression since this can be used also for situations with different products to different consumers (Johansen et al., 2010a). The method is illustrated graphically in Fig. 1.

The analysis was performed with SAS PROC MIXED version 9.1.3 (Statistical Analysis Systems, Cary, NC), using Satterthwaite's approximation for the degrees of freedom.

2.2.2. Fuzzy C-means (FCM)

The idea behind the FCM approach used here is to identify subgroups of consumers with a similar response to the principal com-

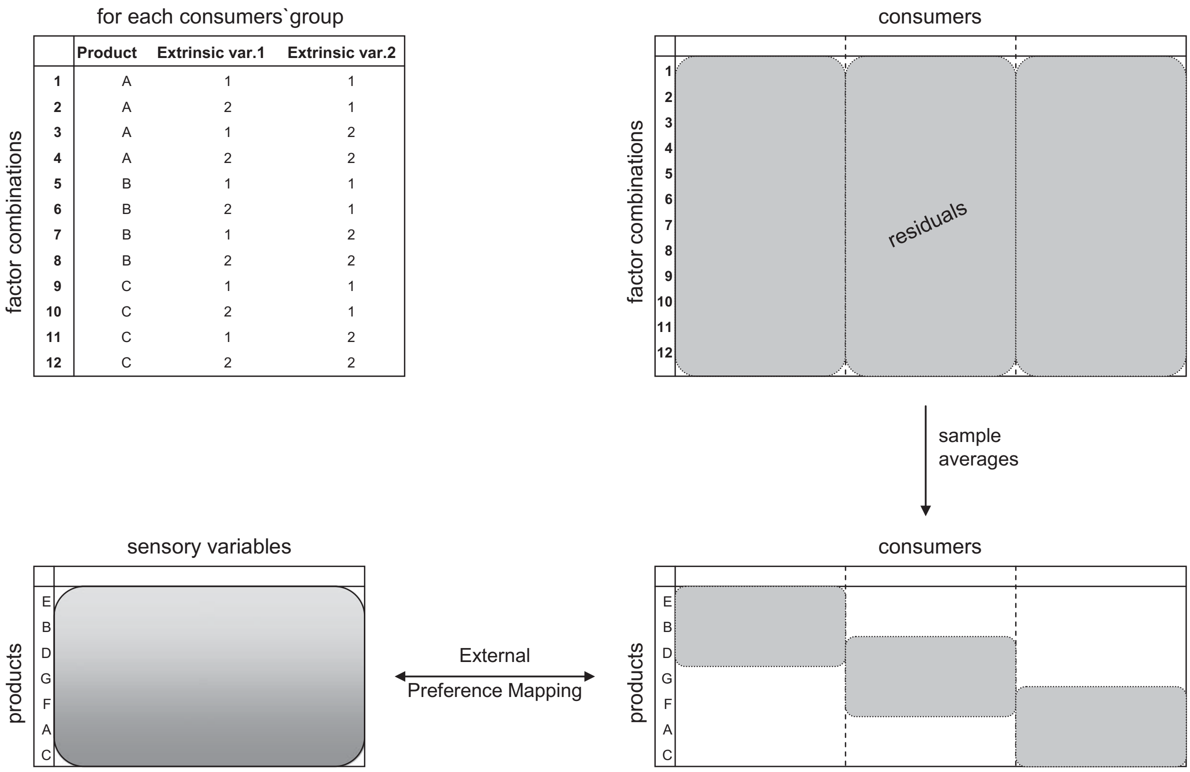

Fig. 1. Proposed approach for analysing individual differences. A full factorial design, different for each consumers' group (because of the different product sets tested) and consisting of 12 ($3 \times 2 \times 2$) factor combinations, is used for each consumer. Once having obtained residuals from the ANOVA/ANCOVA model with only fixed effects, averages over categorical factors are taken for each consumer and each product. Missing values indicate that not all consumers tested all products. Then an external preference mapping with sensory data for all products is run.

ponents from the sensory data and the extrinsic attributes. As has been advocated (Næs et al., 2001; Næs, Lengard, et al., 2010; Næs, Brockhoff, et al., 2010) this can be done by using the residual distance based on a model with extrinsic factors and the principal components from the intrinsic ones. As discussed in Johansen et al. (2010a) this has strong advantages related among others to the fact that different products can be used for the different consumers. The segments will then typically be analysed separately without using the individual contribution, which is an important component in the ANOVA approach above. The idea is that the consumers are already relatively similar and there is less need for a structured random error model.

The fuzzy clustering method used here is based on the fuzzy C-means algorithm (Bezdek, 1981). The underlying idea is that the natural tendencies of clusters or group structure in the data should be expressed by membership values. These values can if wanted be interpreted as probabilities of membership to different groups (Krishnapuram & Keller, 1993). They vary between 0 and 1, indicate the degree of membership for each object to each of the clusters, and their sum for each observation vector to all groups is equal to 1.

Indicating the membership values by u_{ij} and the distances by d_{ij}, the FCM algorithm aims at minimising the following criterion:

$$J = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}^{m} d_{ij}^{2}, \tag{2}$$

where $i = 1, \ldots, N$ corresponds to the i^{th} object, $j = 1, \ldots, C$ corresponds to the j^{th} cluster and m is an exponent called the fuzzifier parameter. Most often it is set equal to 2 (Krishnapuram & Keller, 1996), but other values can also be useful. Johansen et al. (2010a) investigated a procedure for determining the best value of m. In this paper the value of 2 gave reasonable results and no further attempts were made to change it. The minimization of J with respect to the membership values and the distances will favour combination of large values of u and small values of d and vice versa, corresponding to obtaining as clearly separated clusters as possible (Berget, Mevik, & Næs, 2008). The algorithm is described in the appendix. The method ends up with a regression model for each cluster and membership values that are used for allocating consumers to the segments. For each consumer the largest membership value determines which group he/she belongs to.

Choosing the number of clusters is important for regular use of FCM and different measures of cluster validity and strategies for studying the quality of splitting have been developed (Berget, Mevik, Vebø, & Næs, 2005; Bezdek, 1981; Halkidi, Batistakis, & Vazirgiannis, 2001; Næs & Isaksson, 1991). Another and more direct approach is to consider the average absolute residual value of the model used for different choices of C. This approach requires the entire clustering algorithm to be run for each potential value of C. The choice is usually related to the trade-off between a small number of clusters and a small average absolute residual. In this paper we will use a plot of these values to guide us in the decision.

The extrinsic attributes and their levels are the same for all consumers, but the samples are here few and different. A purist viewpoint would then be that, since there are only three products tested by each consumer, one can only do cluster analysis based on the residuals using linear intrinsic attribute models. An alternative viewpoint would be to say that we concentrate on the extrinsic attributes and allow for enough flexibility in the intrinsic attributes so that it does not impose any serious restriction on the clustering. Such a viewpoint will be taken for the analysis conducted here. A quadratic model will be used for the intrinsic attributes, but the results will also be compared to those obtained using only a linear model. Afterwards, one can of course also look at the contour plots of the intrinsic attributes within each group, but then with a more explorative perspective in mind (see also the discussion session).

The calculations were run using self-made algorithm in R software version 2.10.1.

3. Application data set

The data set used for illustration of the method is based on consumer choice probability of orange juices with different sensory properties in combination with two extrinsic attributes: price and processing method. 10 juices were first analysed with sensory analysis by a trained panel of 11 assessors.

Then a group of 105 orange juice consumers were recruited. To ensure sufficient variation across the components to be analyzed, stratified random sampling was performed. The selection and stratification criteria were: (1) each respondent likes orange juice, (2) there is roughly the same percentage of respondents in the age categories 20–42 and 43–65 years old, and (3) there is roughly the same percentage of males and females. The data were collected in a central location test in Norway, summer 2010. To increase the response rate all respondents received a small reward for participating.

First, all the 105 consumers were given all the juices in a blind overall hedonic test of the juices. Scores between 1 (Dislikes very much) and 7 (Likes very much) were given for each of the products. This test was not the primary focus here, but will be used for comparison and validation.

Three sets of three juices in each were then selected according to the PCA scores plot of sensory profile for all ten juices. The primary choice criterion for the selection of product sets was to cover the sensory region as evenly as possible, looking for the maximum spread of products in the first and second dimensions. The PCA scores plot with the selection of three product groups is illustrated in Fig. 2.

In the next part of the study the consumer group was split in three, corresponding to the three groups of products used. Each juice was combined with two extrinsic categorical attributes: production (of two levels: conventional and organic production) and price (of two levels: low, 24.90 NOK and high, 32.90 NOK). The design used for the consumer testing was thus for each consumer a full factorial design consisting of 12 ($3 \times 2 \times 2$) combinations. Note that three different factor combinations were tested by different consumers because of the three juice sets. A traditional full profile conjoint with randomized order of the descriptions was conducted. As an introduction, the respondents were asked to imagine the following situation: "You have gone to the store to buy orange juice for yourself and your family. In front of you 12 different orange juices are displayed. The juices vary according to production method and price". After this introduction the respondents were asked to read each of the 12 factor combination descriptions carefully, and indicate how likely it is that they would choose these juices. More precisely, consumers were asked to rate all 12 combinations for their choice probability on a 7-point Likert scale, anchored with "Very unlikely" and "Very likely" and with a neutral centre point meaning "Neither unlikely nor likely". Independent randomisation was done for each consumer.

4. Results

4.1. PCA of the sensory data

A principal component analysis for the average response over replicates and assessors of the sensory attributes (significant at a level of 0.05) was run; the related scores plot is presented in Fig. 2. Choosing the full cross validation (Martens & Næs, 1989) the first two components together are able to explain 95% (83% and 12%) of the variation in the model; for this reason two components are used in order to select products.

Three sets of three juices each were selected in such a way that the sensory region is covered as evenly as possible and also such that products from different regions are presented to each consumer. The selected sets also are shown in Fig. 2. Note that, in this case, only linear effects are possible for each of the consumers.

The loadings plot (Fig. 3) identifies two clear aspects: the first principal component discriminates clearly between what is often perceived as high and poor quality characteristics concerning odour and taste, while the second component is strongly related to colour features.

From comparing the scores and loadings plots it is clear that juices with the highest intensity of richness, pulp and colour are the ones lying on the first quadrant, while those with metal, artificial, bitter, fermented and packaging tastes or odours lie on the upper left-hand side. The juices in the fourth quadrant are mainly

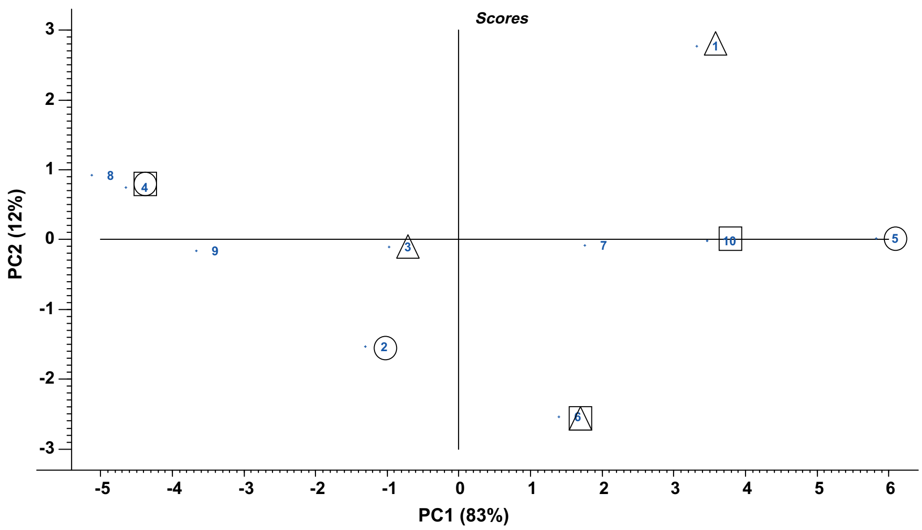

Fig. 2. Scores plot of the sensory analysis for the juice data. The different symbols (triangles, squares and circles) indicate the three product sets tested by different consumers groups.

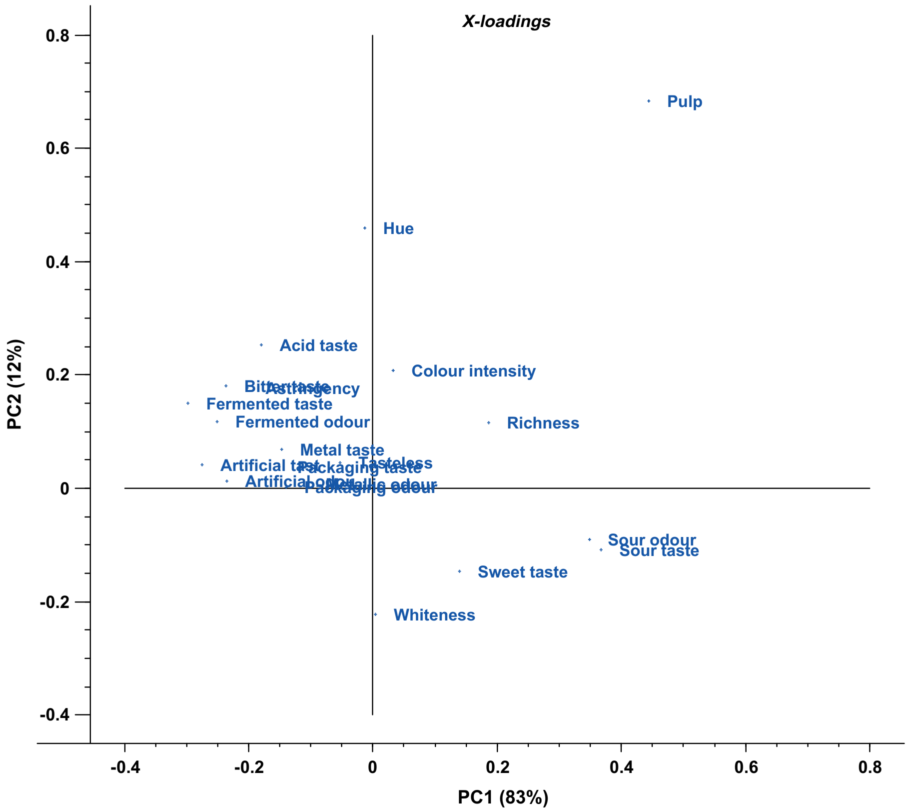

Fig. 3. The loadings plot for sensory data shows the relation between the original sensory variables and the principal components.

sour and with plain colour, while the central juices have less distinctive taste and no particular colour intensity or other dominant sensory attributes.

4.2. Linear preference mapping

A simple linear external preference mapping was performed for the blind tasting data. This was primarily done for giving a rough indication of the direction of liking scores and also for comparison with the results obtained later on. From Fig. 4 it is clear that the majority of the consumers lie in the direction of pulp, richness and high colour intensity and hue, although there are a few also in the other quadrants. No further investigation of these data is attempted here.

4.3. Mixed ANOVA

The PCA of the sensory data also provided input data for the mixed ANOVA/ANCOVA model (equation (1)). The intrinsic attributes are here represented by the first two principal components of sensory data. The other two attributes are price and production, of two levels each. The fixed part of the model used here contains the extrinsic main effects, linear and quadratic effects of the principal components for the sensory data and all two-factor interactions. This means that the linear part of the regression model is allowed to vary with the levels of the extrinsic factors (see Table 1 for a list of the effects). The random effects incorporated in the model were the consumer effect and its first order interaction with all the other factors (see Table 2 for a list of all the individual effects and their corresponding variance components).

As stated above, it was necessary to define a reference level for the two extrinsic attributes. We decided to use low price and conventional production as references (levels number 1 of both factors). This means that the main effects of the intrinsic attributes must be interpreted as their actual effects when the two external attributes are set equal to the reference value. The differences in sensory effects between the different extrinsic factor levels are represented in the interactions. The levels of significance for all effects are shown in Table 1.

As can be seen, price and the first principal component (related to odour and taste characteristics) were strongly significant at 5% level, while production was slightly significant at 10% level. The second component (concerning colour features) was far from being significant at any reasonable level. The main effects plots (Fig. 5) for both price and production highlight that consumers prefer the cheaper products and products made from organic production. The former was clearly expected, but the size of it was not known. The interactions between the first principal component and production and between the first and the second principal components are highly significant for choice probability. The former of these means that in addition to having a significant effect for level 1 of production, the first principal component also has a different effect for the two production types (Fig. 6).

The positive regression coefficient of the first principal component (Table 3) shows a stronger choice probability for those products that lie on the right-hand side of the scores plot. The interaction between the two principal components indicates that for the higher values of the first score the effect of the second component is stronger. The contour plot using only the first two principal components and their interaction is given in Fig. 7. The corresponding plot for the full model (including also quadratic terms) was similar with slightly steeper curves in the corners. This shows clearly a strong choice probability in the first quadrant, which corresponds very well with the first blind tasting preference mapping in Fig. 4. This agreement of results was to be expected and supports the utility of the present approach.

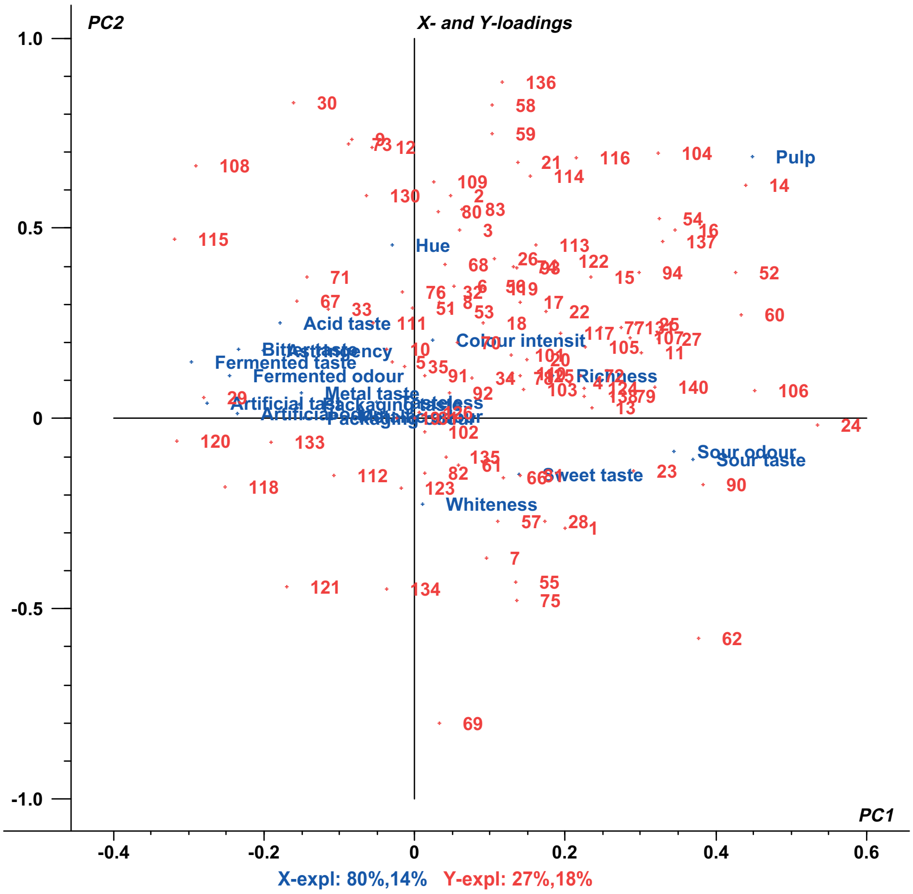

Fig. 4. Linear external preference mapping for the blind tasting data. The X represents the explanatory sensory variables, while the dependent variables (Y) are related to the liking values for each of the consumers.

Table 1
p-Values for fixed main effects and interaction effects on choice probability, according to model (1). The *p*-values are defined with respect to the difference between the reference levels (low price and conventional production) and the alternative levels (high price and organic production).

Variable	*p*-Value
Pc1	0.000
Pc2	0.611
Price	0.000
Production	0.092
Pc1 × Pc1	0.238
Pc2 × Pc2	0.149
Pc1 × Pc2	0.003
Pc1 × Price	0.253
Pc1 × Production	0.010
Pc2 × Price	0.394
Pc2 × Production	0.326
Price × Production	0.944

Table 2
Variance components estimates for the mixed ANOVA/ANCOVA model according to model (1). The variances of the β's as well as the variances of the $\beta \times$ PCs are given.

Variable	Estimate
Cons	0.72
Cons × Price	0.22
Cons × Production	0.22
β_{n1}	0.03
β_{n2}	0.08
$\beta_{n1} \times$ Pc1	0.42
$\beta_{n2} \times$ Pc2	0.16
Residual	1.46

The variance components estimates (Table 2) show that the consumer main effect is able to explain a big share of the variance, while its interactions with the two principal components have a smaller value. The values for the regression coefficients correspond to the variability of the coefficient themselves and one must multiply with an expression for the variability of the components in order to obtain a fair estimate. This was done by calculating the variance of the product of independent variables with zero expectation (i.e. the product of the variances). The main conclusion from all this is that the random noise is dominating, with a strong linear effect of the consumer, but with minor effects of the interactions with the extrinsic conjoint attributes. There is little reason to expect that the interaction effects would be any larger for higher order interactions or more complex intrinsic combinations.

A number of different alternative models for the random part (including and excluding terms) were tested. The *p*-values were slightly different, but from an overall point of view the differences among the population results were relatively small and they all led to more or less the same conclusions.

As mentioned in section 2.2.1, in order to study the individual differences in choice probability one can use the residuals obtained from a model with only fixed effects (Endrizzi et al., 2011). Leaving aside the interactions between intrinsic attributes and consumer

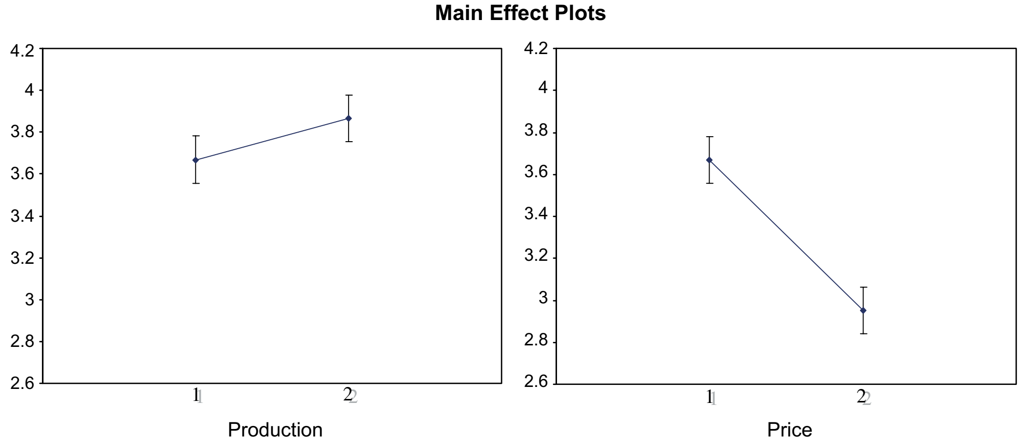

Fig. 5. Main effect plots of choice probability for the categorical factors. The uncertainty bars are related to the Least Squares Standard Errors (equal to 0.1118 for the production levels and 0.1119 for the levels of price).

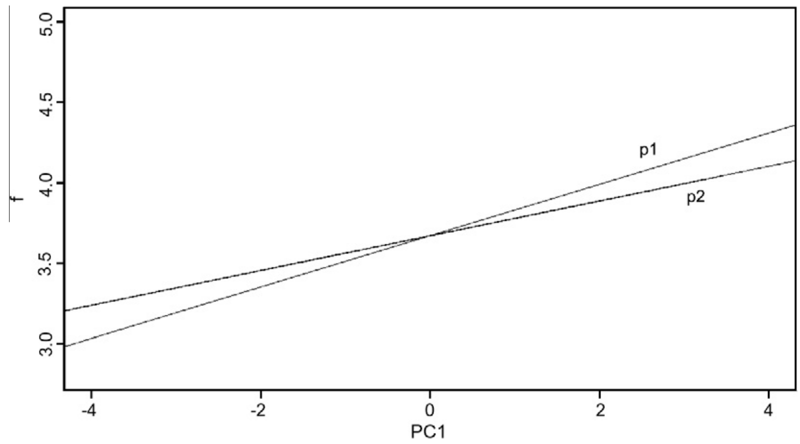

Fig. 6. Regression lines for the production levels (p1: conventional; p2: organic).

Table 3
Regression coefficients for significant effects. Having negative values for Pc1 × Production means that for level 2 of production (organic) the slope is lower.

Effect	Coefficient
Intercept	3.67
Production 1	0
Production 2	0.20
Price 1	0
Price 2	−0.72
Pc1	0.16
Pc2	−0.06
Pc1 × Pc2	0.12
Pc1 × Production	−0.05

effects allowed us to obtain residuals with only the intrinsic information. Averages over categorical factors were taken for each consumer and each product. Note that the residual matrix, organised with consumers as columns and factor combinations as rows, presents a large number of missing values because not all consumers tested each juice. Then an external preference mapping with the sensory data for the selected products was run. Results are shown in Fig. 8. In this case one can see that there is a large variation spread out over the whole area. This reflects the fact that there is a substantial disagreement in choice probability with no clear structure on top of the general tendencies described above. Note that this plot can be used for segmentation, i.e. splitting the groups of consumers into subgroups with a similar response pattern. As is done in Endrizzi et al. (2011) one can superimpose the individual difference (or average residual values for segments) on the population averages in order to get an overall impression of the individual differences in terms of the original measurement scale.

4.4. Fuzzy Clustering

The fuzzy clustering algorithm was run using a model formed by all main effects, all interaction effects and the square of both principal components (the same model as used for ANOVA, see section 4.3). Later on we will compare this with a simplified model.

We started out with testing two clusters (C = 2). Each consumer was assigned to the cluster for which he/she presented the highest u-value. In this case the number of consumers is evenly spread between clusters ($n_1 = 55$, $n_2 = 50$).

The number of individuals from the initial tasting groups in the two clusters is relatively balanced, with the exception of the last tasting group which has a certain bias towards the first (Tasting group 1: $n_1 = 17$, $n_2 = 18$. Tasting group 2: $n_1 = 16$, $n_2 = 19$. Tasting group 3: $n_1 = 22$, $n_2 = 13$). No relation between the calculated segments and randomisation order was detected.

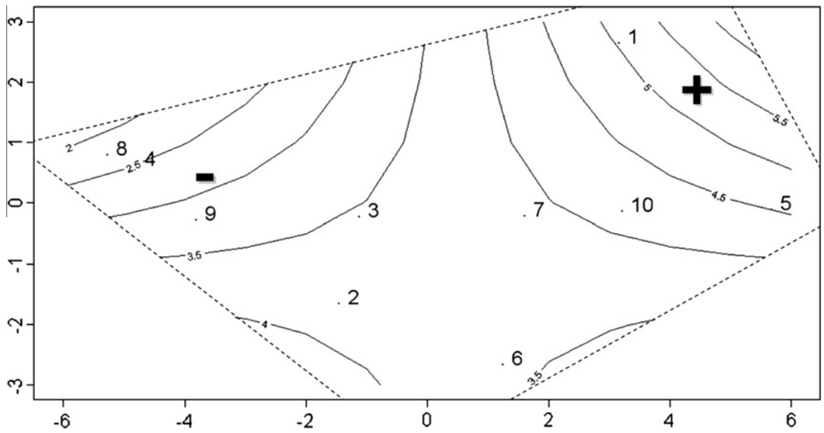

Fig. 7. Contour plot of the first two components and their interaction for the mixed ANOVA/ANCOVA model. Average scores of choice probability and samples are shown.

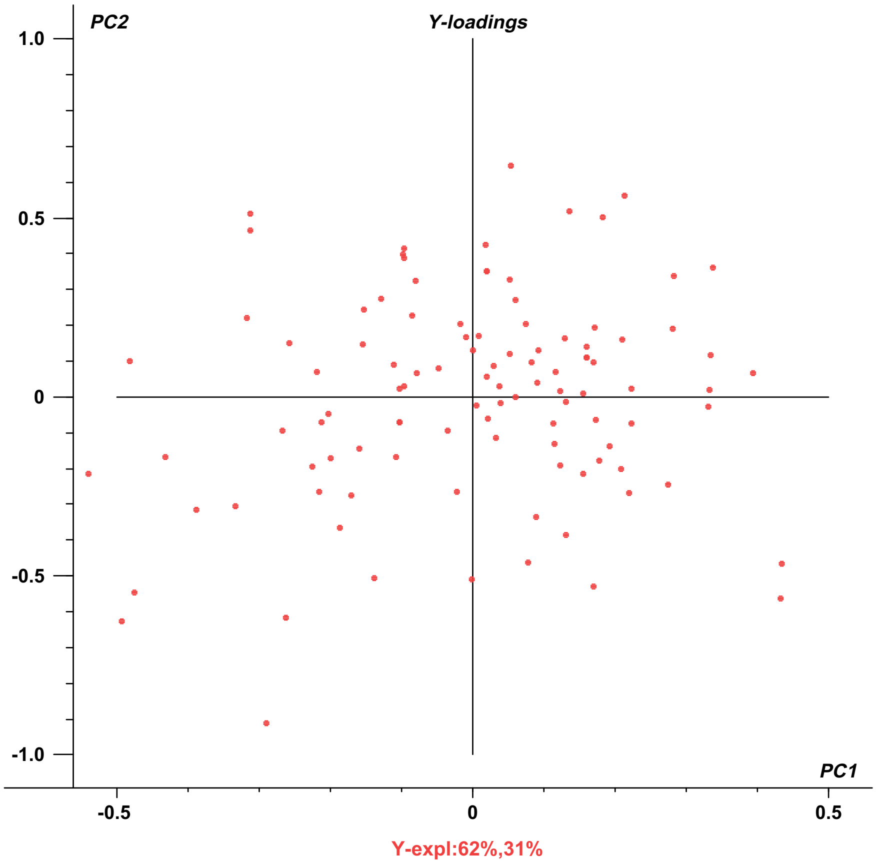

Fig. 8. Results from the analysis of individual differences highlight a large deviation in consumers' choice probability.

An ANOVA model with all main effects, all interaction effects and the square of both principal components is used for testing significance within each group. The results corresponding to the chosen solution are given in Table 4. According to the discussion in Section 2.2.2, main attention should here be given to the extrinsic effects (see also discussion). In the first cluster we can see that the effect of production is strongly positive while it is negative and non-significant in the second. Comparing to the mixed ANOVA results in the previous section, we see that the joint analysis gave a production effect which is about the average, which is natural since the groups are about equal in size. It seems that the segmentation has identified a segment of consumers who are strongly in favour of organic production, while consumers in the other one do not care too much. The effect of price is significant in both segments. A contour plot of the intrinsic attributes gave similar results in both clusters and also quite similar to the average results reported in Fig. 7.

Three clusters were then tested ($C = 3$, number of consumers in each cluster: 35, 37 and 33). Segment one contained only consumers from the first segment when $C = 2$, segment two contained only consumers from the second segment when $C = 2$, while the third segment contained consumers from both. This means that the new cluster is formed by consumers from both while the other two remain more or less the same. For the $C = 3$ segmentation,

Table 4
ANOVA results for two clusters (asterisks indicate different significance levels: ***$p \leqslant 0.001$; **$0.001 \leqslant p < 0.01$; *$0.01 \leqslant p < 0.05$).

Effect	Cluster 1		Cluster 2	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	3.985	<2E−16***	3.173	<2E−16***
Pc1	0.131	0.001***	0.134	0.000***
Pc2	−0.285	0.012*	−0.012	0.908
Price	−0.621	0.001***	−0.824	2.02E−06***
Production	0.499	0.006**	−0.129	0.452
Pc1 × Pc1	0.034	0.002**	0.017	0.089
Pc2 × Pc2	0.023	0.380	0.004	0.862
Pc1 × Pc2	0.170	1.72E−05***	0.131	0.000***
Pc1 × Price	−0.037	0.319	−0.013	0.719
Pc1 × Production	−0.034	0.366	−0.061	0.084
Pc2 × Price	0.023	0.773	0.042	0.576
Pc2 × Production	−0.019	0.811	−0.040	0.590
Price × Production	0.067	0.794	−0.053	0.825

Table 5
Relationship among original tasting groups (rows) and new consumer segments (columns) in the three clusters situation.

	Cluster 1	Cluster 2	Cluster 3
Consumer group 1	14	10	11
Consumer group 2	10	12	13
Consumer group 3	11	15	9

the cluster with significant production effect obtains an even stronger and more significant effect of production, while the second segment still has a non-significant production effect. The new mixed cluster has a non-significant effect of production as well. Table 5 shows how the initial tasting groups spread among the segments in the three-cluster solution.

The process continued with $C = 4$ and $C = 5$. For $C = 4$, one segment is a mix of consumers from all previous groups, while the others seem to have a structure somehow similar to the one when $C = 3$. Two of the four segments present similar membership values. Also with five clusters three segments have similar u-values; moreover four of them are comparable to the groups obtained when $C = 4$ and the last one is empty.

All this indicates that three clusters is a reasonable choice and that further splitting does not provide more information. In order to investigate this further, we computed the average absolute residual value for each C from 2 to 4. As illustrated in Fig. 9 this value strongly drops until three clusters, which supports the results above.

For investigating the stability of the algorithm, different starting membership values were considered. The convergence of the algorithm is obtained every time after a limited number of iterations, typically around 60 for $C = 2$ (with the exception of an initialisation which gave 80 iterations), and 180 for $C = 3$ (however the tendency to the minimum value is detected just after 50 iterations). Convergence properties when $C = 2$ are depicted in Fig. 10. As can be seen, the convergence is quite fast and the same minimum is obtained. The clustering structure is always the same, with very tiny changes in the membership values. Convergence is also good in the situations with four and five clusters: the solution is found approximately with 240 iterations for $C = 4$ and 245 for $C = 5$, but the trend is shown after about 30 iterations.

A comparison was then made between these results and a model with only main effects for the two principal components and their interaction. The quadratic terms were eliminated. For both solutions with two and three clusters the general structure is very similar to the previous model with the exception of few

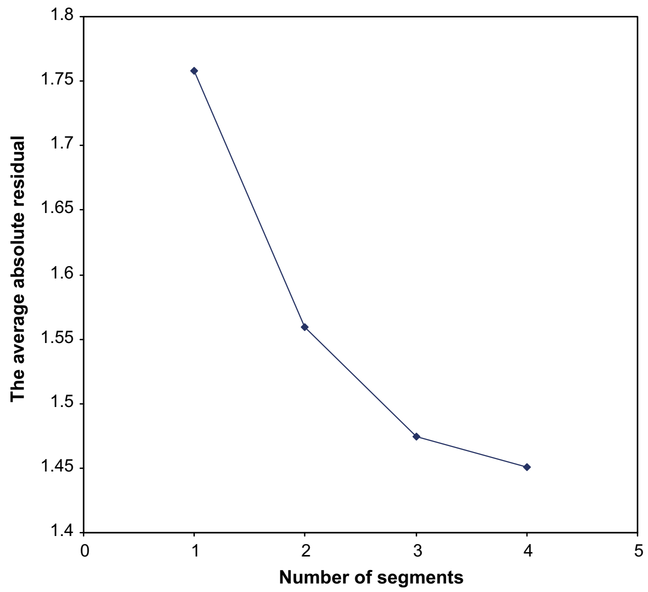

Fig. 9. Average absolute residual values plotted against number of clusters.

consumers: only some of those consumers with weak membership values change segments. Regression coefficients and p-values are comparable. This indicates that the segmentation is very robust with respect to the model used and also that the choice probability structure related to the intrinsic attributes is relatively stable across segments.

5. Discussion

5.1. Combining intrinsic and extrinsic attributes

In this paper we have presented a method which can be used for joint studies of intrinsic and extrinsic attributes. Most often the two types of attributes are treated separately, but this method is one of few existing alternatives that can be used for joint studies. Conducting a joint study has a number of advantages if there are interactions between the two types of attributes. In the present study, an example of such an interaction (although not very strong) is given. The general situation is, however, than one does not know in advance and therefore this approach presents an important opportunity. The aspect of considering combinations is particularly important for basic research studies when the purpose is to understand human perception and choice probability or liking, but can also be important for concrete product development cases in industry.

An additional advantage of this approach is that is can possibly be used for better linking development departments in a company. In our experience, sensory analysis and preference mapping are typically conducted in the product development department while conjoint studies related to extrinsic attributes are done in the marketing or public relations department, often by people with different background and tradition. Using joint studies like the one presented here is a possible vehicle for bringing the two important areas of expertise more closely together.

The method is slightly more complex than standard conjoint and preference mapping studies, but not so much. If ANCOVA is used, the whole procedure can be conducted using combinations of already established methods in standard software packages.

The present approach could also have applications related to other situations in consumer studies where the focus is on combining numerical and categorical attributes (for instance both being extrinsic), not only linking sensory and extrinsic attributes.

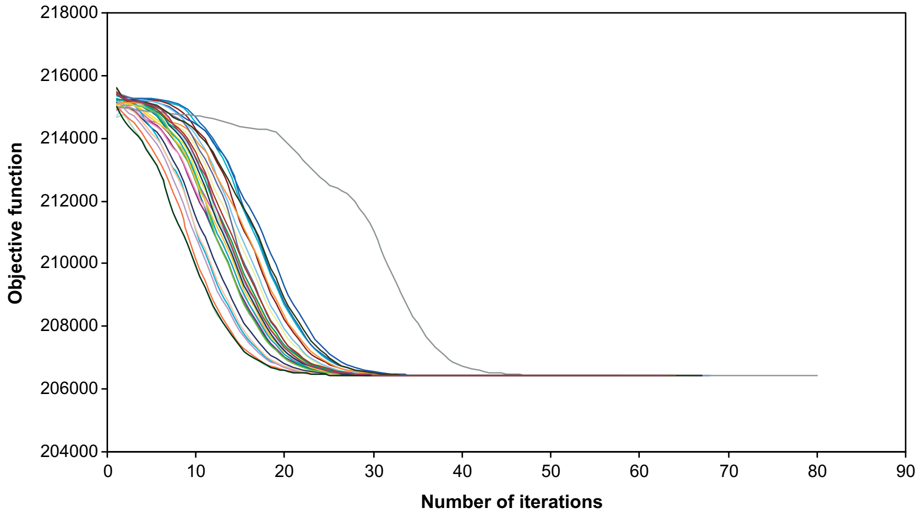

Fig. 10. Convergence properties of the fuzzy C-means algorithm. Objective function for 30 initialisations of the membership matrix.

5.2. Interpreting contour plots for the clusters

The philosophy behind the clustering used was to concentrate on the extrinsic factors and to use a flexible enough model for the intrinsic attributes such that it does not influence clustering so much. In order to test robustness of the procedure, the clustering was done for both a quadratic and a linear model in the intrinsic attributes. The results are similar in terms of clusters obtained and the regression coefficients and *p*-values are comparable. This indicates that in this case the model assumed for the sensory data has limited effect, which is an indication that the model complexity for the intrinsic attributes can be captured by a simple model and/or that the extrinsic attributes are the dominating factors for the clustering. If one believes that the consumer group is actually a combination of subgroups of consumers with similar response pattern to all the attributes tested, one may also look at the intrinsic model for the clusters. There is, however, no way for this approach that one can test the real fit of each consumer to a complex intrinsic model, since there are only three products for each consumer. If this is required, more than three products must be used.

5.3. Incomplete vs. complete designs for the consumers

For large conjoint and other studies it is tempting to decide for an incomplete block design using the consumers as blocks. The methodology presented here is based on an idea of an incomplete design in the sensory scores and the same full (or reduced) design for the categorical extrinsic design variables. A natural question to ask is whether it could be possible to introduce incompleteness for all the variables simultaneously also in this case. Using a standard full incomplete design strategy for all the variables would here require the different samples to be considered as different levels of a single design variable. This can be implemented, but it would give no attention to the aspects emphasised above, related to spanning the sensory space as well as possible for each of the consumers. One could for instance easily end up with one of the consumers testing samples which are very similar to each other. Therefore new method development would be required for this purpose. Another possibility would be to use an incomplete design for each of the consumer groups that test the same samples. How to handle it the best possible way should be investigated. A major issue to discuss would be to treat this in such a way that one would have control over the confounding pattern of the total set.

5.4. The model flexibility for the individual consumers and its effect in the results

In our case we have decided to use only three samples for each consumer. This means that, at an individual level, one only has an opportunity of estimating linear models, and also these with low precision. The average model effect can, however, take on a much more complex model, since the whole area is covered quite well. It was also checked that the individual model complexity has a moderate effect on the results for the population. For the individual residuals analyses this has, however, a limiting effect since only a very broad indication of the major directions is possible. No modelling of the individual ideal points is possible. In order to achieve this one would need at least four samples for the circular model and more if a full ideal point model is to be fitted.

For the FCM strategy, the same considerations are true. For a full modelling of the individual differences, one needs the number of samples per individual that supports the model wanted. But as could be seen in the present example, the segments were quite independent on the model used for the intrinsic attributes.

All these considerations show the dilemma when combining intrinsic and extrinsic attributes. When increasing the number of samples to be tested for fitting more realistic models, the experiment increases substantially. Research should therefore focus on the above, namely how to combine sample selection with an idea of incomplete design for the extrinsic attributes.

The method as it stands now is best suited for estimating population averages and for giving a very broad indication of individual differences.

5.5. A proposal for simplifying the experiment

In the example presented, the same samples were used four times in the experiment, as they were combined with two production and two price levels. This was done without indicating it to the consumers, since each consumer got twelve independent tests. A simplified procedure could be to put the three samples at the table at the same time, and present the twelve questions in randomised order as before. This would give the consumer information about the fact that the same physical sample is used several times. It could produce a bias, but also lead to less noise in the experiment. Research should be conducted in order to investigate the effects of such a procedure.

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Appendix A

An important property of the FCM algorithm is its flexibility with respect to the distance measure that can be used. Usually the distance between an object i and a cluster j is defined to be Euclidean:

$$d_{ij}^2 = \|x_i - v_j\|^2,$$

with x_i the data vector for object i and v_j the prototype vector for cluster j. This implies that the algorithm focuses on detecting spherical clusters. If it is of interest to identify groups of objects with similar linear relationship between a set of predictors X and a response variable Y, another possible distance to consider is the residual distance (Wedel & Steenkamp, 1989; Wedel & Steenkamp, 1991) between the linear functions:

$$d_{ij}^2 = (y_i - x_i^t \hat{b}_j)^2$$

Different regression coefficients $\hat{b}_j$ are used for each group, and they are found as:

$$\hat{b}_j = (X^T U_j X)^{-1} X^T U_j Y,$$

where U_j is the diagonal matrix with weights u_{ij}^m on the diagonal (Bezdek, 1981). The residual distances are particularly useful for regression purposes in consumer studies: intrinsic attributes are incorporated in the X matrix, while the choice/purchase intent or degree of liking is expressed in the Y response. Therefore residuals measure similarity and dissimilarity in consumer choice probability or liking of the product variables.

In this case the FCM algorithm is slightly modified: since each consumer tests different products and since the u-values suggest the consumer segments, rows in the U matrix related to the same consumer must be identical. The algorithm can therefore be summarised like this

1. Initialise the matrix of membership values $U^{(0)}$. For repetition $l = 1,2,\ldots$
2. Compute the residual distances $d_{ij}^{(l)}$ for given $U^{(l-1)}$
3. Take the sums of the distances over P products within the Q consumers ($P \times Q = N$ observations).
4. Update membership values for given $d_{qj}^{(l)}$: $u_{qj}^{(l)} = \frac{1}{\sum_{k=1}^{C} (\frac{d_{ij}}{d_{ik}})^{2/(m-1)}}$, where $q = 1, 2, \ldots, Q$
5. Obtain the original dimensions for the membership matrix U and the distance matrix D by repeating each row P times.
6. Calculate the criterion J until convergence, i.e. until: $|J^{(l)} - J^{(l-1)}| < \varepsilon$.

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Paper III

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Analysing relations between specific and total liking scores

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The objective of this article is to present a new statistical approach for the study of consumer liking. Total liking data are extended by incorporating liking for specific sensory properties. The approach combines different analyses for the purpose of investigating the most important aspects of liking and indicating which products are similarly or differently perceived by which consumers. A method based on the differences between total liking and the specific liking variables is proposed for studying both relative differences among products and individual consumer differences. Segmentation is also tested out in order to distinguish consumers with the strongest differences in their liking values. The approach is illustrated by a case study, based on cheese data. In the consumer test consumers were asked to evaluate their total liking, the liking for texture and the liking for odour/taste.

1. Introduction

In consumer liking studies one is typically interested in both identifying the product that maximises consumers' liking (Ares, Varela, Rado, & Giménez, 2011; Lagrange & Nordback, 1987; McEwan, 1996) and in obtaining information about which properties that are important for the liking (Bi, 2012; Bi & Chung, 2011; Johansen, Næs, Øyaas, & Hersleth, 2010; Menichelli, Olsen, Meyer, & Næs, 2012). The latter is relevant both for the purpose of improved understanding of the liking pattern and for further optimization of the product properties.

A number of methods are commonly used for this purpose. Among them, the self-explicated tests are the simplest and are conducted by just asking people about which properties they appreciate in the products tested. These are not necessarily inferior to other methods used (Sattler & Hensel-Börner, 2003) but they require a mental processing that is not always favourable. More advanced studies such as conjoint analysis (Green & Rao, 1971; Green & Srinivasan, 1978; Moskowitz & Silcher, 2006) and preference mapping (McEwan, 1996; Næs, Brockhoff, & Tomic, 2010; Schlich & McEwan, 1992) have been developed for assessing the liking for various combinations of properties with subsequent data analysis to reveal the drivers of liking.

Preference mapping (Carroll, 1972; Green, Halbert, & Robinson, 1968; McEwan, 1996; Næs et al., 2010; Schlich & McEwan, 1992) is a very useful method in sensory and consumer science in order to understand the relations between intrinsic product properties and liking. It consists of characterising the sensory properties of a set of products using a trained assessors' panel and asking consumers to rate their liking of the same products. Then both data sets are combined by regression analysis to identify the sensory characteristics of the ideal product(s) (van Trijp, Punter, Mickartz, & Kruithof, 2007). In so-called external preference mapping (Carroll, 1972; van Kleef, van Trijp, & Luning, 2006) one considers the first two principal component dimensions of the descriptive data and looks at the relation between these and the liking. An alternative is to do it the other way round through internal preference mapping, using principal component analysis (PCA) of the liking data as the point of departure. For a comparison of the two approaches we refer to Helgesen, Solheim, and Næs (1997).

A possible problem with the mentioned methods, and in general all the methods seeking drivers of liking, is that both the sensory data and the consumer liking data are totally dependent on the actual products used in the analysis. Replacing some of the products by other alternatives could possibly change conclusions about what are the main drivers of liking and which attribute combinations that are the most favourable from a consumer's point of view. Let us imagine, for instance, that for a set of tested products the texture and taste properties are by chance highly correlated, but only the taste is strongly related to the liking. It could be that the actual taste combined with another texture profile would be even more liked. This would not be possible to see from the analysis results, but could have been obvious from an alternative set of products. Moreover the standard methods do not provide

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information about the importance of the different aspects of the liking. Is it the taste which is important or is it the texture that drives the consumer liking? Trained assessors provide a large profile of attributes, but it is not at all obvious that all these attributes are relevant for consumers (ten Kleij & Musters, 2003).

In the light of all these aspects, a possible additional approach is to ask consumers to evaluate both the total liking and the liking of different product attributes (Bi & Chung, 2011; Moskowitz & Krieger, 1995; Mueller, Osidacz, Francis, & Lockshin, 2010; Olsen, Menichelli, Sørheim, & Næs, 2012). This approach will also depend on the actual products considered and does not directly solve the problem mentioned, but its advantage lies in the fact that such an approach can provide additional information about the most important aspects of liking. This means that it can also be used to identify possible alternative combinations of attributes with a potential for an even higher liking. This type of information may possibly enable the product developer to increase the consumer liking by developing more favourable attribute combinations of the product, as will be discussed in this paper.

This paper presents a case study based on semi-hard cheese, where the total liking data are extended by incorporating liking for odour/taste and texture. The paper is methodologically oriented and the main purpose is to propose and evaluate some new ways that this type of data can be approached and analysed, in order to reveal the additional information wanted. The proposed methods are based on new ways of using standard techniques such as principal component analysis and regression methods. The focus of the presented methodology will be on identifying products and consumer combinations for which the different liking variables, or so-called modalities, show a different pattern. The obtained results will then finally be used to indicate what types of further product development that can be proposed for the actual tested example and to show that this information adds to the information already obtained by standard preference mapping.

2. Theory and methodologies

In the following we give a brief overview of our proposed analysis procedure for the type of liking data considered in the paper. The first two points are related to providing a basic and overall understanding of the sensory and liking data. These results are required for understanding better the products and their liking. The next three points (3, 4 and 5) are incorporated for investigating similarities and differences among the three liking variables, both with respect to the relative positioning of the products and with respect to individual differences in the weight the consumers assign to them. First of all a preference mapping is used for each liking variable, afterwards a procrustes analysis is run in order to obtain a more precise measure of the relative differences between the liking variables and the products. Then a regression model is used for analysing how the different consumers vary in their weighting of the more specific variables when they assess the total liking. The rest of the study (points 6, 7) focuses on the difference between total liking and the liking for texture, which is the specific liking variable deviating most strongly from the total liking. One can thus identify those products and those consumers for which the liking of the specific variable and the total liking are most different. Finally, these results are used for segmentation and plotting of liking profiles in the different liking segments.

1. First of all, a PCA of the sensory panel data is run in order to obtain insight into differences and similarities among the products.
2. Then a plot of the average liking values for each product (over consumers) is created in order to achieve an indication of the possible differences among products for the different liking modalities.
3. The internal preference mapping of each liking variable provides an additional valuable tool for understanding differences and similarities.
4. Generalised procrustes analysis (GPA) is then run for the purpose of comparing the scores from the different preference maps.
5. For a better understanding of the importance of each specific liking variable in explaining the total liking, regression models that relate the total liking to the liking of the other sensory attributes are implemented.
6. Thereafter a strategy for indicating which products are similarly or differently perceived by which consumers is proposed. The method is based on calculating the differences between total liking and each of the specific liking variables. Individual differences among consumers and the correspondence between the total liking and the specific liking values can then be elaborated through a PCA of the difference values.
7. Segmentation is finally tested out in order to distinguish consumers with the strongest differences in their liking values. Plots of the average profiles in each segment offer an immediate graphical interpretation of the differences.

In the following a brief description of each building block of the proposed methodology is given.

2.1. Principal component analysis of the sensory data

The PCA (Mardia, Kent, & Bibby, 1979) is always useful in an early phase of an investigation for providing an overview of the data. It enables understanding of which products are similar and which products are different according to the different measured sensory attributes.

2.2. Average values of the liking variables

The average values for each product (taken over consumers) and for each liking variable give insight into similarities and differences in the general preference profile for each liking attribute. If consumers are very different (Næs et al., 2010), one needs to support these plots by PCA plots taking individual differences into account, as will be discussed below.

2.3. Internal preference mapping of the liking variables

Preference mapping (Carroll, 1972; Helgesen et al., 1997; van Kleef et al., 2006) is a term used for relating the liking of a number of products to descriptions of the products, typically obtained by sensory analysis. Internal preference mapping (mdpref), which is used in the present paper, is based on first running a PCA on the consumer liking data and then regressing each sensory attribute linearly onto the first few principal components (here two) using the model

$$y_k = q_{0k} + q_{1k}t_1 + q_{2k}t_2 + e_k. \quad (1)$$

The y_k describes a sensory attribute, the t's are the first two PCA scores from the consumers liking data, e's are the residuals and the q's represent the intercept (usually equal to 0 because of the centring in PCA) and the coefficients (different for each attribute) for the consumer scores. External preference mapping on the other hand is based on the same type of model structure, but in that case the principal components (i.e. the t's) are obtained from the sensory data and the Y's correspond to the different consumer liking values. Since our focus is on consumer data and not on sensory data, internal preference mapping is here chosen. Non-linear models and interaction models are possible within the same framework (McEwan, 1996; Myers & Montgomery, 1995).

Preference mapping focuses on relative differences between the products. The primary use of preference mapping in this paper is to investigate how differently the products are liked relative to each other for the different liking variables. We also focus on how the different segments of consumers relate to this general underlying structure.

2.4. Generalised proctrustes analysis on the mdpref scores

The generalised procrustes analysis (GPA) is an iterative method that focuses on reducing the difference between two or more matrices **Y** using a transformation based on translation, rescaling and rotation (Dijksterhuis, 1996; Gower, 1975). These elements can be summarized in the following way:

$$\mathbf{D}_p + c_p\mathbf{Y}_p\mathbf{H}_p. \tag{2}$$

where the $\mathbf{Y_p}$'s are the original data matrices (products as rows and variables as columns), the $\mathbf{D_p}$'s are the matrices representing translation constants (eliminated with centred columns), the c_p's are the scalars representing the rescaling and the $\mathbf{H_p}$'s represent orthogonal rotation matrices. A criterion measuring the difference between the transformed matrices is then optimised and the average or the consensus matrix is computed.

The GPA is in this paper used for giving more precise measures of the similarities among the liking variables and the products. The scores of the different preference mapping solutions for the liking variables are thus compared. The **Y**'s above represent the score matrices for the considered liking attributes (three in our case). Main focus is given to the sum of squares of the GPA residuals, obtained according to product and to liking attribute, but a plot of the consensus scores with some of the products highlighted will also be given.

2.5. Relations between liking scores

In order to understand better the individual differences in the relative weighting of the two specific liking attributes on the total liking, a simple linear regression analysis (Montgomery, Peck, & Vining, 2006) is run for each consumer separately. The model used is

$$y^{\text{total}} = a + by^{\text{odour/taste}} + cy^{\text{texture}} + e, \tag{3}$$

where y^{total}, $y^{\text{odour/taste}}$ and y^{texture} describe the dependent total liking and the independent specific liking variables respectively (Moskowitz & Krieger, 1995). The intercept a will in this paper be removed since each of the variables is centred for each consumer before the regression. We also divide each variable by its standard deviation before running the regression, in order to obtain comparable regression coefficients. In order to check for collinearity, the variance inflation factor (VIF) is calculated for each individual regression, in order to identify and remove those consumers with high collinearity (i.e. VIF >10) between the liking variables. The regression coefficients for the remaining consumers will be plotted in a scatter plot. For completeness, also a full regression analysis of all consumers is conducted. In that case also the interaction term between the two specific liking variables is incorporated. Collinearity is also checked by the use of the VIF.

2.6. PCA on the difference matrices

The next step is to construct matrices based on differences between the liking variables, with products representing the rows and consumers the columns. Element-by-element differences are calculated between total liking and each of the other specific liking variables (Table 1). Then the un-standardised PCA is applied on the difference matrices. Since PCA is based on column centred data, interpretation of the PCA plot is not as obvious as usual in this case. The reason is that positive and negative input values for PCA cannot directly be interpreted as either positive or negative differences between the liking scores (e.g. between total liking and texture liking, which will be in focus here). If for instance one assessor has only positive differences, he will end up with negative values as input to PCA for those products for which the positive differences between total liking and texture liking are the smallest. If an assessor has only negative liking differences values, the negative input values for the PCA (i.e. negative centred values) will correspond to the largest negative differences before centring. For the positive centred values, similar comments can be made. In other words, the interpretation of positive and negative values after centring is somewhat mixed. For each consumer, however, the interpretation is that negative centred values represent those products for which texture liking has the most favourable value (among the products) as compared to the total liking. Likewise, for each consumer positive centred values represent those products for which total liking has the most favourable value as compared to the texture liking. These aspects are illustrated in Fig. 1, which shows how positive and negative values after centring relate to three consumers with a different pattern among the liking values.

The PCA can also be done for the differences between the specific liking variables, but here we will concentrate on the differences between total liking and one of the specific liking attributes only (texture liking).

To aid interpretation it may sometimes be useful to compute average individual differences over products for each consumer. The distribution of these averages is thus used to assess for instance whether the largest negative values for PCA are generally due to negative initial differences between the liking values or to small differences. A more detailed study of the differences values for each consumer, as will be done below (Section 4.6), can also be used to give even more precise information on the liking patterns.

Finally, it is possible to relate the scores of the principal components to the sensory attributes for the same products, in order to enhance interpretation.

2.7. Segmentation of the consumer group

PCA loadings from the previous analysis can be used to segment or split the consumer group into subgroups. For illustration this is here done by splitting the consumer group according to the first principal component, which represents most of the variability in the data set. In principle other possible segmentation strategies can also be used, depending on which aspects one is interested

Table 1
Theoretical matrix of the differences between the total liking (tl) and the specific liking (sl) for each ith product (prod) and each jth consumer (cons), with $i = 1,\ldots,n$ and $j = 1,\ldots,m$. The difference matrix is used in the PCA in order to identify which products are liked similarly or differently by which consumers.

	cons_1	cons_2	···	cons_j	···	cons_m
prod_1	$\text{tl}_{11}-\text{sl}_{11}$	$\text{tl}_{12}-\text{sl}_{12}$	···	$\text{tl}_{1j}-\text{sl}_{1j}$	···	$\text{tl}_{1m}-\text{sl}_{1m}$
prod_2	$\text{tl}_{21}-\text{sl}_{21}$	$\text{tl}_{22}-\text{sl}_{22}$	···	$\text{tl}_{2j}-\text{sl}_{2j}$	···	$\text{tl}_{2m}-\text{sl}_{2m}$
···	···	···	···	···	···	···
prod_i	$\text{tl}_{i1}-\text{sl}_{i1}$	$\text{tl}_{i2}-\text{sl}_{i2}$	···	$\text{tl}_{ij}-\text{sl}_{ij}$	···	$\text{tl}_{im}-\text{sl}_{im}$
···	···	···	···	···	···	···
prod_n	$\text{tl}_{n1}-\text{sl}_{n1}$	$\text{tl}_{n2}-\text{sl}_{n2}$	···	$\text{tl}_{nj}-\text{sl}_{nj}$	···	$\text{tl}_{nm}-\text{sl}_{nm}$

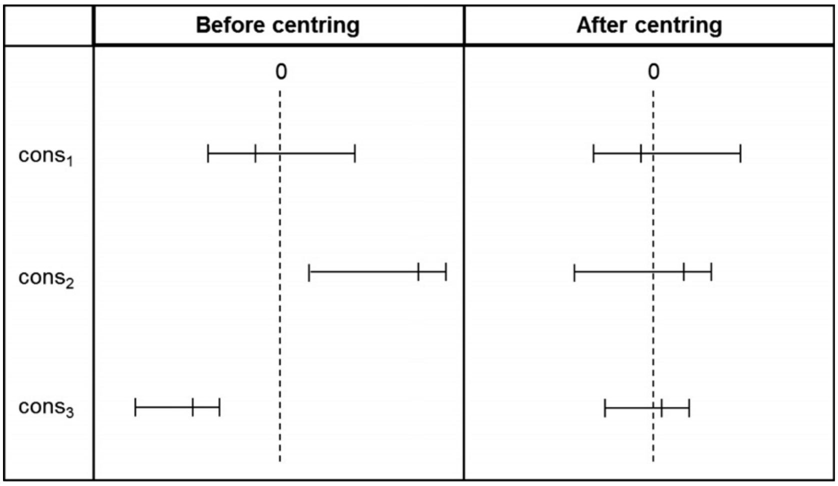

Fig. 1. An illustration of three different consumers and their differences between total liking and texture liking for three products (i.e. the little vertical lines). For the first consumer ($cons_1$), the difference is both positive and negative, for the second ($cons_2$) all the liking difference values are positive and for the last ($cons_3$) all the liking difference values are negative. After the centring, all consumers end up with both positive and negative values. This illustrates how to interpret the positive and negative values after centring.

in highlighting. For illustrating the different segments, average liking values in each group for both total liking and the specific liking attributes are plotted, interpreted and compared to the overall plot for all consumers.

3. Data set

The data set used in this study is based on a product development experiment for a new semi-hard cheese variety. A total of 12 cheeses were analysed by sensory analysis, some of them being commercial products and some others being experimental products. From the 12 cheeses, 7 were selected for the consumer test. This was done by using a PCA of the sensory data and by selecting products covering the scores space.

3.1. Sensory data

Descriptive sensory analysis was performed using an internal, trained panel of 6 assessors. The methodology is more thoroughly described by Kraggerud et al. (Kraggerud, Solem, & Abrahamsen, 2012). After a calibration session, each of the 18 sensory attributes were evaluated using a continuous scale from 1 to 9, the scores were thus averaged over assessors.

3.2. Consumer data

A consumer home use test was also conducted (Norway, Stavanger area). Consumer selection criteria were: (1) over 15 years of age, and (2) frequent user of cheese (more than once a week). 189 respondents participated in the test. All 7 cheeses were packed in neutral vacuum packages of 200 g with three-digit codes. The consumers were asked to consume the cheese in the way they would normally do, and test all cheese products in the same manner. A paper questionnaire was enclosed with the products, for writing notes during the tasting if needed. In the questionnaire the order of the questions was according to a random order design. The degree of liking of each product was evaluated for odour/taste, for consistency and from an overall point of view, using a discrete 9-points hedonic scale with defined end-points (1 = dislike extremely, 9 = like extremely). Other questions were also included in the questionnaire, filled in through internet, but these are not affected in the paper.

4. Results

4.1. Principal component analysis of the sensory data

From the PCA scores plot for the covariance matrix of the sensory data (Fig. 2) we observe that products number 7 and 1 (and also 6, 3 and 4) have similar sensory properties since they are close to each other, while for instance products 2 and 4 are very different in their sensory profiles. Product 2 is strongly connected to the first dimension, being in contrast with all the other products. In the loadings plot this first component seems to be most strongly related to texture properties, while the second axis is related to both odour/taste and texture. One reason for the first factor's focus on texture is that there are many texture variables in the data set. The aromatic, grainy, elastic and hard-to-chew cheeses lie on the left hand side of the scores plot (in the direction of products 2 and 5) while the pasty ones (for instance 4) are on the right. Bitter and hard cheeses with high intensity of odour and flavour are the ones in the first quadrant (1, 7); salty, sour and soluble cheeses are to the lower right-hand side (6, 3).

4.2. Average values of the liking variables

The average preference values presented in Fig. 3 highlight the most liked and disliked products for the liking variables. In general the three liking variables show a similar general trend, with a strong exception for products 5 and 7. For both odour/taste and total liking, the two products have a much lower degree of liking than for texture, for which all products, except product 2, have a high and comparable liking score. From the sensory space presented in Fig. 2, it can be seen that this product has clearly the highest values of elasticity, firmness on chewing and grainy and the lowest values of pasty, solubility and flavour intensity. The products 5 and 7, for which the differences are the largest, are quite different in their sensory properties. Thus it seems that there are products in the data set for which the texture is fine, but the odour/taste can be improved in order to achieve a better total liking. These products will be given a special attention throughout the

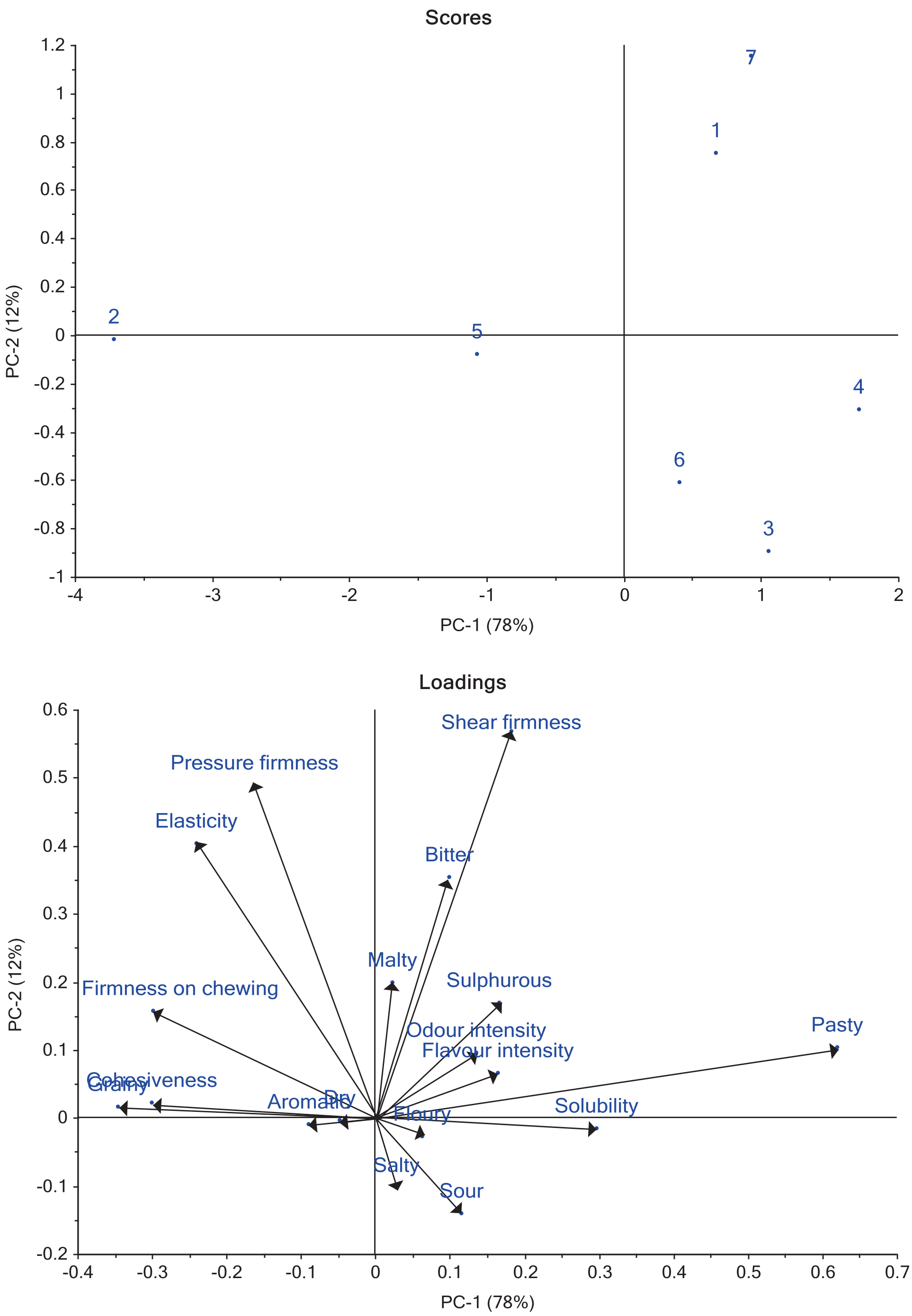

Fig. 2. Scores and loadings plots for the sensory data.

paper. In particular we will look at how they are perceived by different consumer segments.

4.3. Internal preference mapping of the liking variables

To further investigate the differences between the three liking modalities, we performed a preference mapping for each variable separately. The main aim is to give a visual interpretation of the liking structures and also to try to highlight some deviating patterns among them. For total liking (Fig. 4a) the explained variances for the first two components are 45% for the X (consumer data) and 21% for the Y (sensory data). Even though there is a large disagreement among the consumers, it seems that for total liking the majority of consumers lie on the upper side of the plot. According to a comparison with the sensory loadings, they are in the direction of those cheeses with the highest intensity of sour (and to a certain extent aromatic) and the lowest intensity of bitter, elasticity, pressure firmness. Products number 7 and 2 are in the opposite direction, with fewer consumers. This means that these two products are overall disliked, corresponding quite well to the average results. Above the origin, where most consumers are, we find products 1, 3, 4, 5, 6 which all (except 5, which is located in the middle) lie on the right side in the sensory space (Fig. 2).

For the odour/taste liking the results were comparable (Fig. 4b). One can see that the only clear difference is that the two axes are rotated. This means that the importance of the two axes is some-

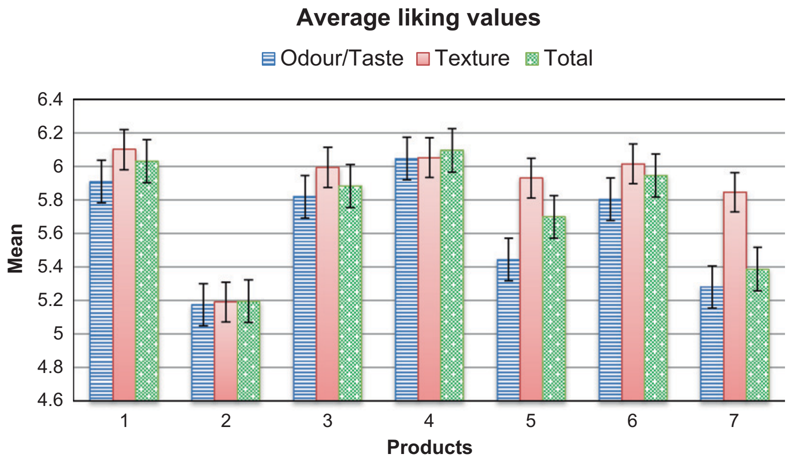

Fig. 3. Average values and standard errors of the products for each liking variable.

what different for the two liking variables but, as can be noticed, the explained variances for the two axes are fairly similar. For texture, however, the situation differs: the consumer loadings (not shown) indicate that the majority of consumers are situated in the direction of products number 1, 3 and 6 in the score plot. The least preferred cheese is clearly the number 2, characterised by elasticity, pressure firmness and firmness on chewing. This corresponds fairly well to the average results (Fig. 3).

4.4. Generalised procrustes analysis on the mdpref scores

The GPA is then used to give a more concise measure of the differences between the three mdpref score plots (based on the two plotted components only). The sum of squared residuals for GPA after fitting (Fig. 5a) is here split and visualised according to object (product) and configuration (liking variable). Product number 7 is clearly the one with the highest sum of squared residuals, followed by products 2 and 5, which seems to be in good correspondence with the preference mapping results. The sums of squares of the residuals for the three configurations show that the odour/taste variable and the total liking match the consensus much better than texture, again indicating the strongest disagreement between total liking on one side and texture liking on the other. In order to illustrate the differences between a product with a large sum of squared residuals (i.e. product 7) and a product with a small sum of squares (product 6), the GPA consensus and the individual configurations for these two products are given in Fig. 5b.

4.5. Relations between liking scores

The inspection of the VIF values for each individual regression led to the removal of 21 consumers. The regression coefficients for the rest of the consumers (161 consumers, 7 were previously removed by standardizing) are presented in Fig. 6. As can be seen, there are large individual differences in how the consumers weigh the two specific attributes when determining their total liking. The tendency, however, is that the odour/taste has generally a larger regression coefficient than the texture and is thus the most important in determining total liking. This is confirmed by the simple counting of the number of consumers on each side of the 45 degree line in the plot (99 on the lower side and 62 on the upper side). More specifically, the average values for the coefficients of odour/taste and texture are 0.857 and 0.653 respectively, corresponding quite well to the overall results (presented in Table 2) from a linear model comprising the two liking variables and their interaction. In the multiple regression for all consumers the VIF values are very small (Table 2), indicating that in this case there is no serious collinearity of the predictors that can yield misleading coefficients (Moskowitz & Krieger, 1995).

4.6. PCA on the difference matrices

This next step pertains to looking at the differences between the total liking and the variable with the strongest discrepancy, namely liking of texture. First of all, we computed the average differences for each consumer and plotted them in a histogram (not shown) as described above. The majority of the values were between −1 and 1 with a clear clustering around 0. A more detailed study of the distribution of differences revealed that 28 consumers had only values greater than or equal to 0, 45 consumers had only difference values less than or equal to 0, 91 consumers had both positive and negative difference values, while 25 consumers had a difference value of 0 for all products. Therefore, in this case, all the three possibilities in Fig. 1 will be represented. Anyway, as already emphasised (Section 2.6), for each consumer the negative centred values to PCA always represent those products with the most favourable values for texture liking relative to total liking, and vice versa for the positive values. We refer to the description in Section 2.6 for further discussion and interpretation.

The PCA is considered on the difference values (between total liking and texture liking) collected in a matrix with products as rows and consumers as columns (see Table 1). From the PCA results for these difference values (Fig. 7) we note that there is a wide spread of consumers, meaning that the texture liking and the total liking differ in different ways for the consumers. Here we will be mainly interested in products and consumers lying away from the centre. The consumers to the right and the left in the plot are in this case mainly consumers which have the largest centred difference values between total liking and texture liking. The products that create this most important contrast are 2 and 5 on one side and product 7 on the other.

As mentioned previously, the position of the products in the space can in addition be explained in relation to the sensory properties related to the attribute under study. In this case (Fig. 7c) it seems that both component directions are related to more or less the same attributes with some exceptions (pressure firmness, for instance). This information can be useful for understanding better how the differences relate to the sensory attributes. As an example, for those consumers lying on the right hand side of the loadings plot, the (centred) total liking minus the texture liking is positive for products (i.e. product 2 and 5) which have a high degree of cohesiveness and graininess (corresponding to Fig. 2).

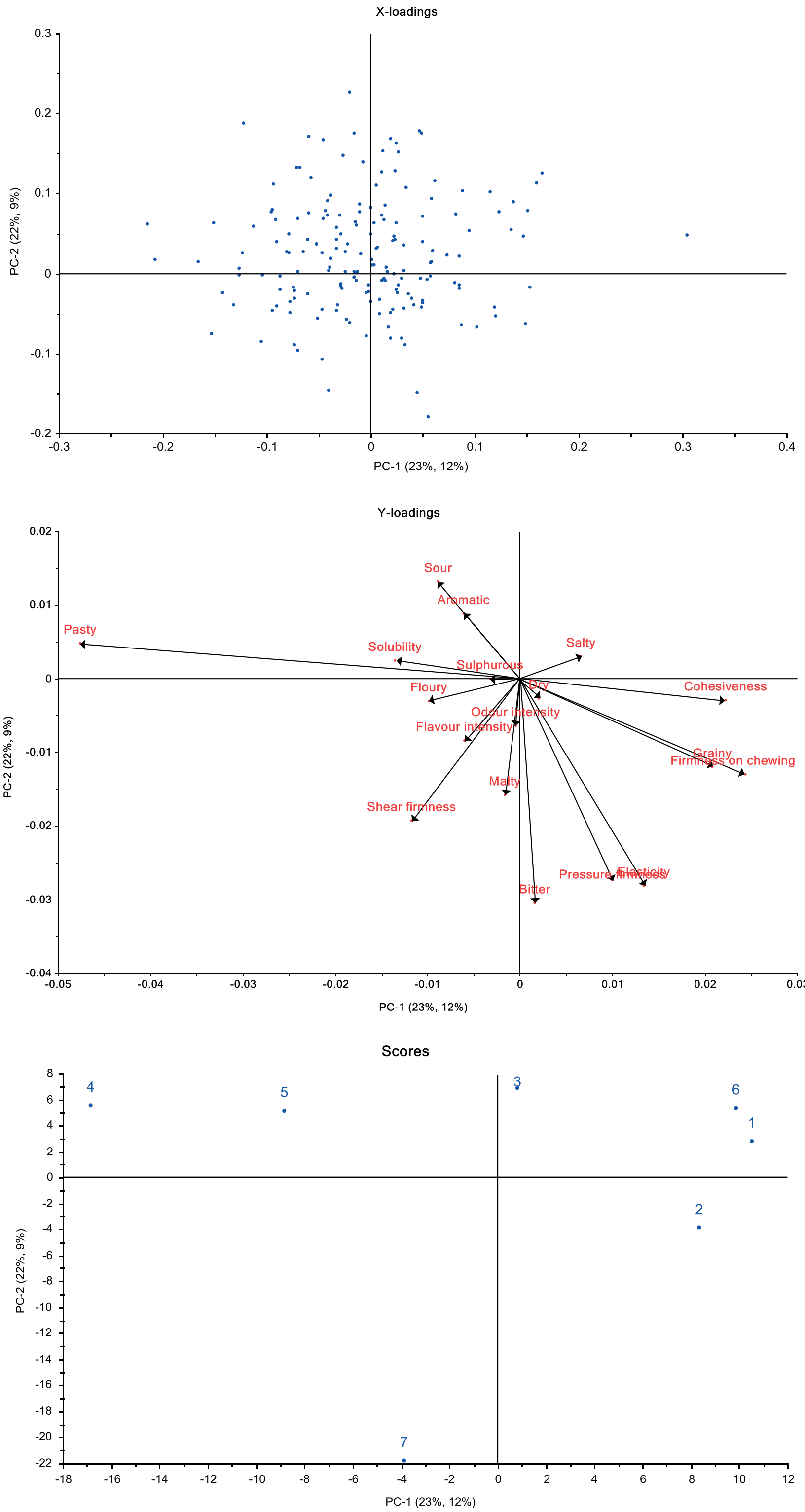

Fig. 4a. Internal preference mapping results for the total liking variable. The first two principal components explain 45% (23% + 22%) of the variability in the consumer data and 21% (12% + 9%) of the variability in the sensory data.

4.7. Segmentation of the consumer group

For the purpose of visualising the groups of consumers more clearly, we decided to split the consumer group (Fig. 7b) in three, one segment to the left, one in the middle and one to the right, thus the splitting is for the axis with the largest explained variance. By splitting in this way we obtain 41 individuals in the group to the left, 48 individuals in the group to the right and 75 in the middle group (25 consumers were removed owing to the zero differences for all the products, see also above). The middle group is less interesting and will thus be disregarded here because of the smaller span of the scores. Note that this splitting in segments is here just used as an example for visualising results and other ways of splitting into subgroups could also have been tested.

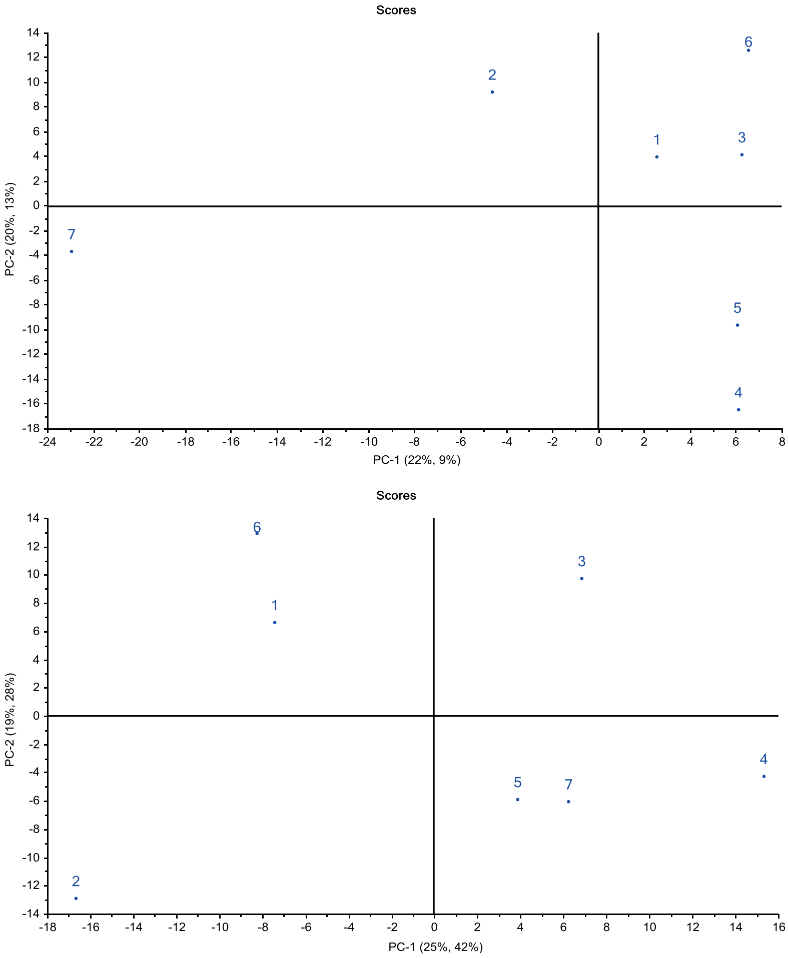

Fig. 4b. Odour/taste and texture score plots from internal preference mapping.

In order to characterise the segmentation, we consider the averages over consumers for the raw liking values for the two extreme groups. For texture, the most dominant differences are for products 2, 5 and 7 (Fig. 8), i.e. the extreme ones along the first dimension of the PCA scores plot (Fig. 7a). In fact these products are the only ones perceived in a completely opposite way by the two groups: in the first cluster the total liking for product 7 is the highest and the texture liking is the lowest. For the second cluster the situation is the opposite, with a huge difference between total liking and the liking for texture for the same product. The opposite is true for product 2. Product 5 is instead the cheese with the biggest gap between the two liking variables (i.e. the highest texture liking and almost the lowest total liking) for those consumers on the left hand side of the PCA plot. The second consumer group does instead not find any difference between texture and overall liking for the same product. We can also see that in group 2 the liking differences for products 2 and 7 are evident, while almost all the other products are evaluated in the same way for texture liking and total liking. In other words, the splitting into segments changes the overall results in Fig. 3 completely for some of the products.

In particular the product 7 seems to be very interesting. It is the most overall liked in group 1 and the least liked in group 2, but for the texture it is close to the opposite. In the discussion we will consider further how this type of information could possibly be used for suggesting further product development.

Through segmentation one can thus highlight specific consumer groups with different preference patterns, in terms of which products are preferred and which property is liked the most for the different products. In some cases it is also possible to identify products that, although being liked/disliked similarly on average for all the liking variables, may be liked differently for different consumer groups.

5. Discussion

5.1. The use of different liking variables: methodological aspects

The main aim of this study was to investigate the relation between total liking and liking for odour/taste and texture. In previous research different methods have been used for this purpose. Most often a multiple linear regression model of the same type as in Eq. (3) is used (Ares, Barreiro, & Giménez, 2009; Moskowitz & Krieger, 1995; Olsen et al., 2012). It should be mentioned that in consumer studies of this type multicollinearity can be a problem. In this paper we have used the VIF to test it and remove those consumers with a severe collinearity, but other approaches also exist (see e.g. Martens and Næs (1989) for an overview). For methods dealing specifically with this type of data we refer to Bi and Chung (2011), where the focus is on determining proper weights for assessing the relative importance of the regressor variables in situations of multicollinearity. A comprehensive review of statistical methods for research on the topic is available in (Bi, 2012). These methods, however, focus only on average population effects, but can probably be modified for individual consumer analyses as well. The most common result is that odour/taste is the main driver of total liking, followed by texture and appearance (Moskowitz & Krieger, 1995; Olsen et al., 2012).

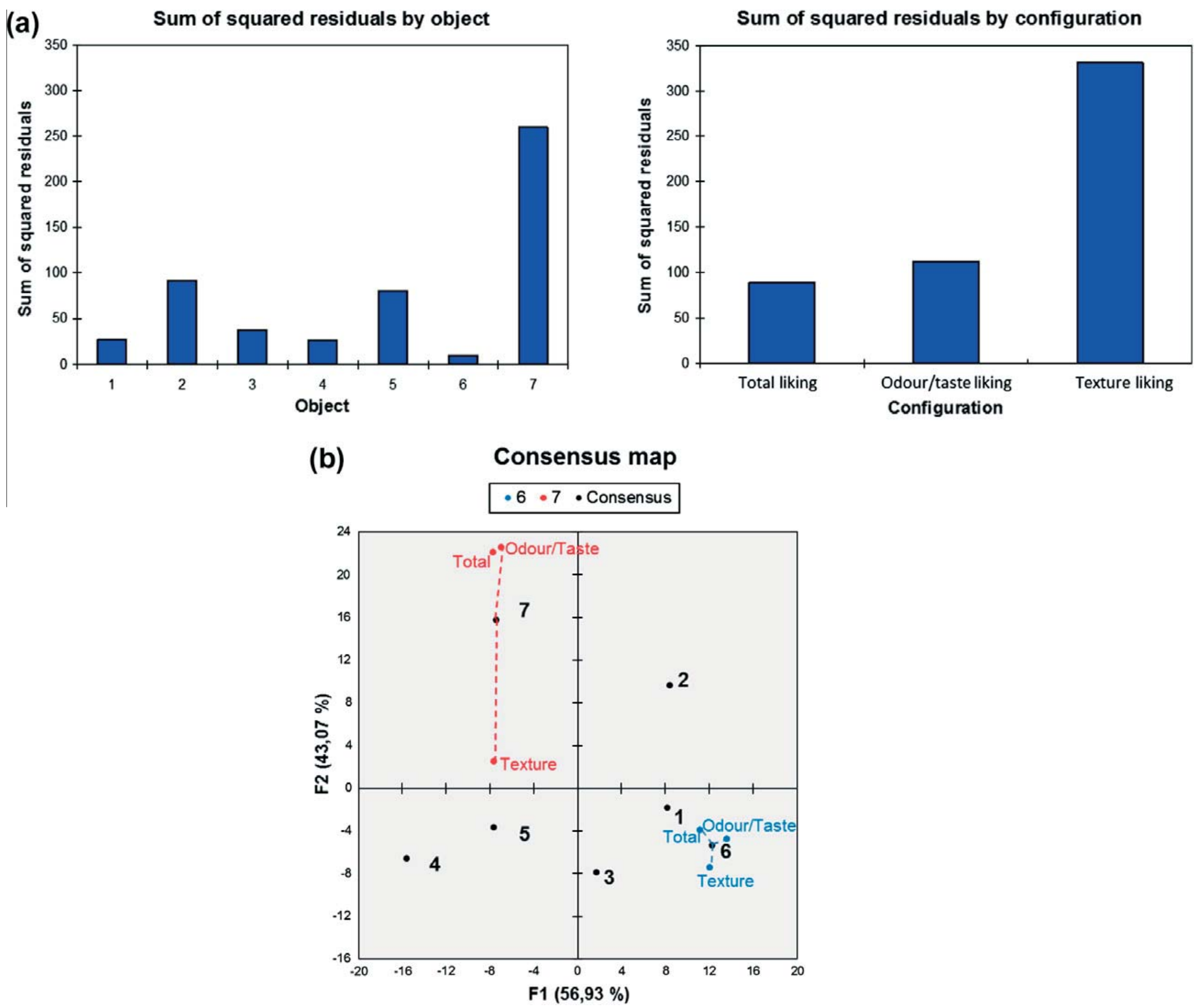

Fig. 5. Sum of squared residuals after generalised procrustes analysis (a) and consensus map (b), obtained for each product and for each liking attribute. The results are obtained from the first two PCA scores from the internal preference mapping.

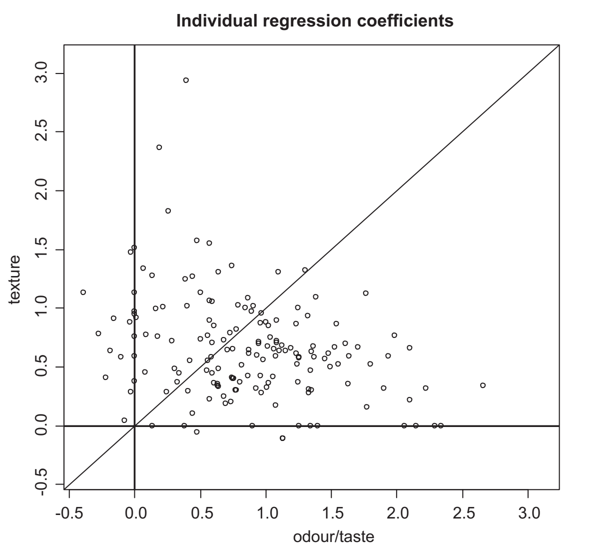

Fig. 6. Scatter plot of the regression coefficients for the individual regression models.

Table 2
Standardised regression coefficients, standard errors, *p*-values and variance inflation factor values for the specific liking variables in modelling the total liking (based on all consumers).

Term	Coefficient	Standard error	*P*-value	VIF
Texture	0.6427	0.0172	<2e-16	1.7644
Odour/taste	0.9068	0.0171	<2e-16	1.7441
Odour/taste * texture	0.0476	0.0130	0.0003	1.0156

Our results indicate a similar trend, with a clear dominance of the effect of odour/taste.

The complexity of food may make it difficult to distinguish between the different liking variables. For instance, the evaluation of odour liking can be influenced by the appearance of the product. This type of effects can be taken into account considering interaction terms in a multiple regression model, as done in this paper. In this case, the interaction was, however, very small at a population level (see Table 2).

These regression methods are useful, but do not take into account individual differences among consumers. This can be done as proposed here by calculating a regression model for each individual

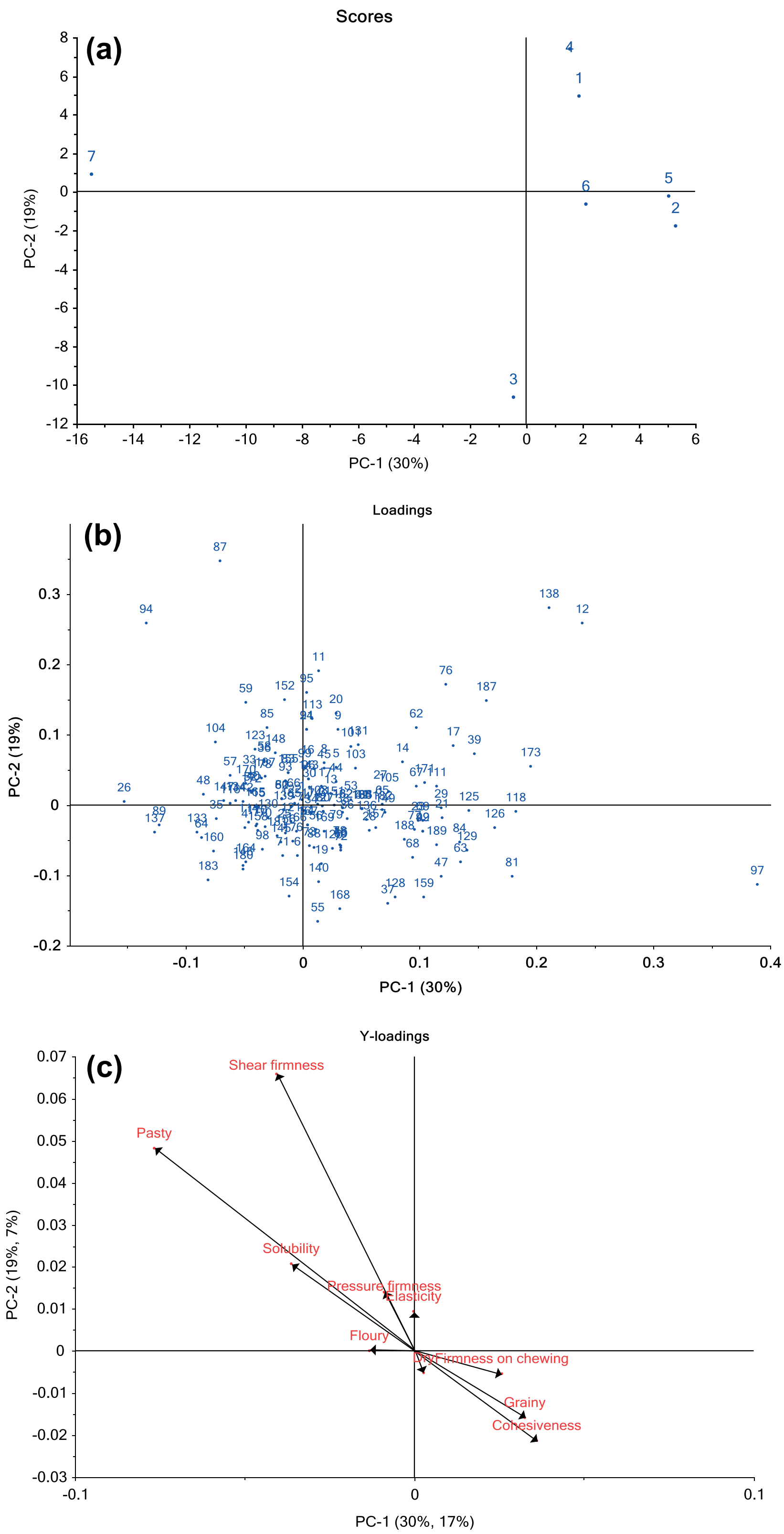

Fig. 7. Scores plot (a) and loadings plot (b) from the PCA of the differences between total liking and texture. A loadings plot of the texture sensory variables (c) is added by PCR in order to characterise the differences.

(see also Moskowitz & Krieger, 1993). These differences can be more or less pronounced in relation to the type of product considered, since for instance a product might have a small range of variation in texture but a large range of variation in taste.

Anyway, as far as we are aware of, individual differences have not previously been studied in connection with relative differences among products when liking for different modalities has been in focus. In this paper it has been shown that, even though a specific

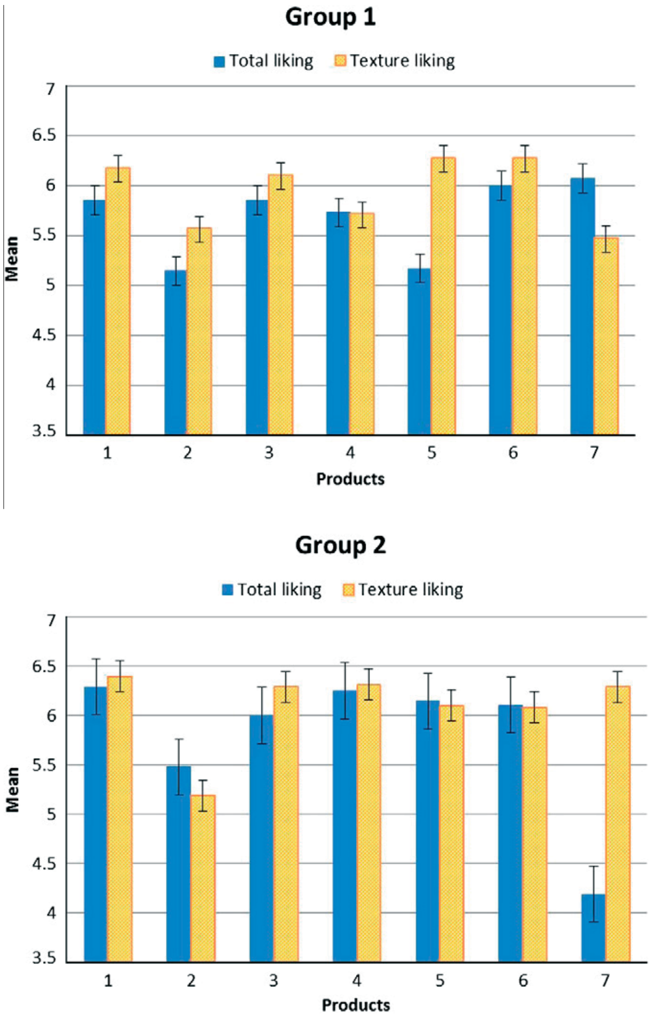

Fig. 8. Product means and mean standard errors for the total liking and the texture liking in each segment of the PCA loadings plot (Fig. 7b).

attribute liking for two products is the same on an average level, two groups of consumers can have a completely different evaluation. For these reasons we have here proposed some new techniques based on difference matrices and plotting that can be used to provide this type of insight. This new statistical approach is able to identify both products and consumers for which the liking values for different attributes deviate the most.

It should finally be noted that the segmentation of consumers in the last step of the proposed approach can be done in the way the researcher finds most suitable for her/his purposes. In this paper the approach is graphically oriented and based on the PCA of the difference matrices. By using this type of plot it was possible to identify groups for which the relations between the total liking and the specific liking for a product are very different. By regressing the sensory data onto the PCA components through PCR, we could also determine which sensory variables are linked to the liking or disliking of the variables. This means that one can also use these results to predict what needs to be improved in a product.

5.2. Identification of the drivers of liking

It should be mentioned that all methodologies based on measuring liking of different modalities depend on the assumption that it is possible for the consumer to distinguish between and articulate their view on different liking variables (Lawless & Heymann, 2010). It is beyond the scope of the present paper to go in depth on this issue, but we refer to Lawless and Heymann (2010) for a discussion of it.

Another and related aspect to take into account is whether one should ask the consumer about the liking of very specific attributes or only about quite broad and general categories as done here. There are different opinions on this among researchers (Moskowitz, 2001). One possible viewpoint is that the majority of the product data should be acquired through expert panels, with consumers only rating a few liking attributes. Another one is that consumers can assign many different liking attribute ratings for the same product.

In this and previous studies it is clear that the various properties of a product are evaluated and weighted differently in their contribution to the total liking. Thus it is also quite clear that liking is at least not uni-dimensional (Moskowitz and Krieger, 1995). Few studies have, however, been conducted for uncovering the real dimensionality of the liking attributes (Moskowitz, 2001; Moskowitz and Krieger, 1993; Moskowitz and Krieger, 1995). In particular in Moskowitz (2001) consumers were asked to answer to questionnaires comprising many different liking ratings. Results revealed that the major dimensions (by means of PCA) for the actual products are related to broad sensory categories such as appearance, odour/taste and texture. Despite the lack of sufficient literature on the topic, the available results advise that many of the individual liking ratings are redundant. We thus suggest the use of broad categories for the liking attributes, as done in this paper.

5.3. Product development and maximisation of consumer liking

For complex products like cheese many characteristics can affect consumer liking. The present paper has shown that liking for different aspects of the products can vary strongly among different consumer segments. The different evaluations of the specific properties are generally not visible (Section 4.2) if only total liking is considered or if only total averages over the population are used.

In order to maximise consumer liking, one possibility for the researcher is thus to look at similarities and differences between liking modalities. Following the procedure suggested in this paper it is possible to understand better why a product obtains a low total liking. The results may also propose possible ways of improving the product properties.

For instance, for one of the consumer groups considered in our study (Fig. 8) product number 7 is the most liked overall, but its texture is the least liked. Thus the product developer could possibly improve the total liking of this product further by trying to modify the texture in the direction of the products with a more favourable texture property. In this example a possibility could be to improve the texture properties of product 7 in the direction of those of product 6 (i.e. firmness on chewing). It thus seems that, for segment number 1, a combination of product 6 and 7 could be a good suggestion for further product development. For the second segment, it seems that the total liking is so low for this product that it is not worthwhile trying to improve it. All these results are difficult to read from the standard preference mapping results of total liking which means that the proposed approach gives additional insight into the liking patterns.

6. Conclusions

In this paper we have discussed an approach for investigating the relation between different liking variables for cheese, i.e. the liking of different so-called modalities. The study has proposed and shown the potential of a methodology based on standard tools such as PCA and regression. Focus has been on the relation between average results and individual differences. Furthermore a strategy based on the differences between total liking and specific liking is proposed, in order to indicate which products are similarly or differently perceived by which consumers. The study is graphically oriented. The study concludes by suggesting some possible paths for further product development that are difficult or impossible to reveal based on the standard methodology of preference mapping.

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Paper IV

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Alternative methods for combining information about products, consumers and consumers' acceptance based on path modelling

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ABSTRACT

In consumer studies the collected consumer data are often of different nature (demographic variables, attitudes and habits). Usually these data are considered all together when modelling consumer acceptance patterns, even though there may exist interesting relations between groups of consumer characteristics. The objective of this paper is thus to propose methodology for relating the different types of consumer characteristics data to each other and to the consumers' acceptance, when also product information is available. Focus is given to the possible approaches for pre-processing and combining data sets with different dimensions in a path modelling context. Considerations about advantages and limitations are given. The study is general in nature and can be applied to preference mapping, conjoint analysis and their combination. The different approaches are illustrated by data from a consumer test on chocolate, comprising several types of information about consumers.

1. Introduction

In consumer studies in the food sector a major issue is to identify the most important factors for consumer acceptance. Conjoint analysis (Green & Rao, 1971; Green & Srinivasan, 1978; Gustafsson, Herrmann, & Huber, 2003; Louviere, 1988) is an important technique for revealing the effect of various product attributes on consumers' liking. If focus is put directly on the relation between product sensory profiles and acceptance data, preference mapping is often used (McEwan, 1996; Næs, Brockhoff, & Tomic, 2010; Schlich & McEwan, 1992). A few studies have also been conducted for combining the information about both intrinsic (sensory) and extrinsic (additional) product attributes (Enneking, Neumann, & Henneberg, 2007; Helgesen, Solheim, & Næs, 1997; Johansen, Næs, Øyaas, & Hersleth, 2010; Menichelli, Olsen, Meyer, & Næs, 2012).

When interpreting consumer acceptance data, either in conjoint analysis or in preference mapping studies, one is interested both in the average population effects of the product attributes as well as in the individual differences in liking and how these relate to consumer characteristics like attitudes, values and/or demographics (Benton, Greenfield, & Morgan, 1998; Endrizzi, Menichelli, Johansen, Olsen, & Næs, 2011; Olsen et al., 2011). The focus in this paper will be on individual differences and how different consumer characteristics are linked to liking patterns, when also product information (i.e. intrinsic and/or extrinsic attributes) is available. In particular, data from a consumer test on chocolate will be considered for investigating how specific consumer characteristics, i.e. demographics and attitudes to chocolate (Benton et al., 1998), are related to the acceptance of specific chocolate products.

The most important statistical methods aiming at incorporating consumer characteristics data in conjoint analysis are explained in detail by Næs, Lengard, Johansen, and Hersleth (2010b). Usually, one distinguishes between analyses that incorporate consumer characteristics in the primary data analysis and methods that first analyze the liking pattern and then relate the individual differences to consumer characteristics afterwards. The first of these options is most easily handled by incorporating consumer characteristics, such as gender and age, directly into an ANOVA model together with the conjoint factors. Particular interest is in the interactions between the consumer characteristics factors and the conjoint factors, which give insight into how the different consumer groups perceive the differences between the products. This approach is valuable, but there is usually a strong limitation on the number of consumer characteristics factors that can be handled at the same time. It is therefore often more useful to analyze the individual differences directly by some type of multivariate analysis, based either on the raw data, the regression coefficients from individual ANOVA models or the residuals from a joint ANOVA model (Endrizzi et al., 2011; Næs, Aastveit, & Sahni, 2007). If regression

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coefficients from individual ANOVA models are used, one has a choice between considering all coefficients or only one or a few of them (Næs et al., 2010b). Regardless of what is used as a basis for analyzing the individual differences, the consumer attributes are then related to these values by using regression analysis, for instance partial least squares (PLS) regression (H. Martens & Næs, 1989). A regression method has also been developed for analyzing consumer characteristics, consumer liking data as well as their relation to the design of the experiment in one single analysis (L-PLS, see Martens et al., 2005). The L-PLS method is based on the singular value decomposition of products of the three data sets involved and provides essentially four different scatter plots (products, design variables, consumer hedonic scores, additional consumer attributes). The method contributes to the methodology of PLS regression, but only few applications have been reported (Martens et al., 2005). It is not obvious whether it is generally better to use two-step or one-step procedures for linking this type of data. Other "L-based" methods can be found in Lengard and Kermit (2006), in Endrizzi, Gasperi, Calòb, and Vigneauc (2008) and in Vinzi, Guinot, and Squillacciotti (2007).

All the regression-based methods mentioned above treat all the consumer characteristics in a parallel way. This may be useful, but sometimes the consumer characteristics represent different features, for instance demographics, attitudes or habits. In such cases one may also be interested in a deeper insight in how the different consumer characteristics relate to each other and also in whether an effect is so-called direct or indirect (i.e. through another variable) (Bollen, 1987, 1989). This type of insight can be obtained by using some type of structural equations modelling (SEM, also called path modelling). This approach does not seem to have been tested before for linking together product properties (Bech, Juhl, Hansen, Martens, & Andersen, 2000; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005), consumer acceptance data (Olsen, Menichelli, Sørheim, & Næs, 2012) and consumer characteristics (Guinot, Latreille, & Tenenhaus, 2001).

The aim of this paper is thus to propose and investigate methodologies for incorporating different blocks of consumer characteristics information, where each block is a data set defined as a collection of related characteristics. The data sets have very different structure and dimensionality and it is not obvious how to combine them in such a multi-block SEM context. The main focus will therefore be on how to combine data sets with different columns and rows in a path modelling framework. In some cases, the links between the blocks in a SEM context are set up according to a hypothesis of causal relations, but such a perspective is not necessary for applying the methods. An example of this is given in Næs, Tomic, Mevik, and Martens (2011) and Martens, Tenenhaus, Vinzi, and Martens (2007), where the focus was on relating different modalities of a sensory profile without any clear causal relation between them. It is important to emphasise that the methods proposed in this paper for organising the data are applicable regardless of which perspective is taken.

There exist different approaches to model estimation in path modelling, but for illustration in this paper PLS path modelling (PLS-PM) is used (Tenenhaus, Pagès, Ambroisine, & Guinot, 2005; Vinzi & Russolillo, 2013; Vinzi, Trinchera, & Amato, 2010), because of its simplicity in use and its strong focus on individual differences (scores) (Wold, 1979, 1985). For the structures presented below any other of the available estimation method can be used, for instance SO-PLS (Jørgensen, Segtnan, Thyholt, & Næs, 2004; Næs et al., 2011) and LISREL (Jöreskog, 1978; Jöreskog & Sörbom, 1989). More specifically, two different approaches will be proposed and tested on a data set from a consumer study of chocolate. The study is general in nature, focussing on strategies for organising and centring the data as well as different ways of analysing the relations between blocks. The focus will be on principles of how to combine data and what types of information that can be gained in the two cases. Considerations about the possibly most relevant and suitable approach will be given. Weaknesses and strengths of a path modelling approach as compared to a regular PLS regression modelling of all attributes in a parallel way will be highlighted.

2. Materials and methods

2.1. Data set

2.1.1. General structure of the considered data sets

For the following discussion it will be assumed that one has available three different types of data (Fig. 1a). The first data set consists of information about J products, related to the design of the experiment or to sensory or chemical variables, resulting in a data set of dimension J times K, where K is the number of product attributes. The second data set consists of M consumer characteristics for each of the L consumers, representing for instance demographics, attitudes and/or habits. Finally the third data set is formed by acceptance scores for each of the L consumers for each of the J products. This data set can include only overall liking data (as is the case here) or it can incorporate Q different types of acceptance data, related for instance to particular sensory modalities, specific eating contexts or various meal combinations. In this paper we consider only the situation in which the same products are served to all consumers, but the methodology can be generalised to cases in which different consumer groups evaluate different products (Menichelli et al., 2012). Fig. 1b highlights the relations between the data sets and also emphasises the "L-shape" of the data structure used for the development of the L-PLS method (Martens et al., 2005).

2.1.2. Data set for illustration: consumer test on chocolate

The data set used for illustration of the methods is based on a consumer acceptance test. Three chocolates were evaluated. Chocolate number 1 is a market leader in its category, while chocolates 2 and 3 are new and under development by a competitor. A group of 248 chocolate consumers were recruited. The criteria for participation in the test were: (1) respondents are evenly distributed according to age (in the 20–60 range) and gender (roughly the same percentage of males and females), (2) each respondent likes chocolate, and (3) each respondent eats chocolate at least twice a week.

In this paper informed liking is considered, i.e. consumers tasted each chocolate while observing a picture displaying chocolate brand and some additional information about taste and texture properties. Product 1 was not depicted by words, since it is a well-known product in the market. Product 2, which is new, was described to have "a clear cocoa taste and good sweetness", while product 3 (also new) was presented as "a powerful and rich" chocolate. These descriptors correspond well to the sensory properties for both chocolates (product 2 has a marked cocoa and sweet taste and also cocoa odor, product 3 is mainly related to fatness). All the 248 consumers evaluated their acceptance of the different types of chocolate on a 9-point hedonic scale, anchored with "Like not at all" and "Like very much" and with a neutral centre point "Neither like nor dislike". Products were presented in a randomized order.

After tasting the chocolate, the consumers were asked to fill in a questionnaire which included socio-demographic and attitudinal questions. In particular consumers indicated their agreement on a scale from 1 to 7 for selected statements from the "Attitudes to chocolate questionnaire" (Benton et al., 1998). Altogether, 10 statements representing attitudes for craving and guilt were considered.

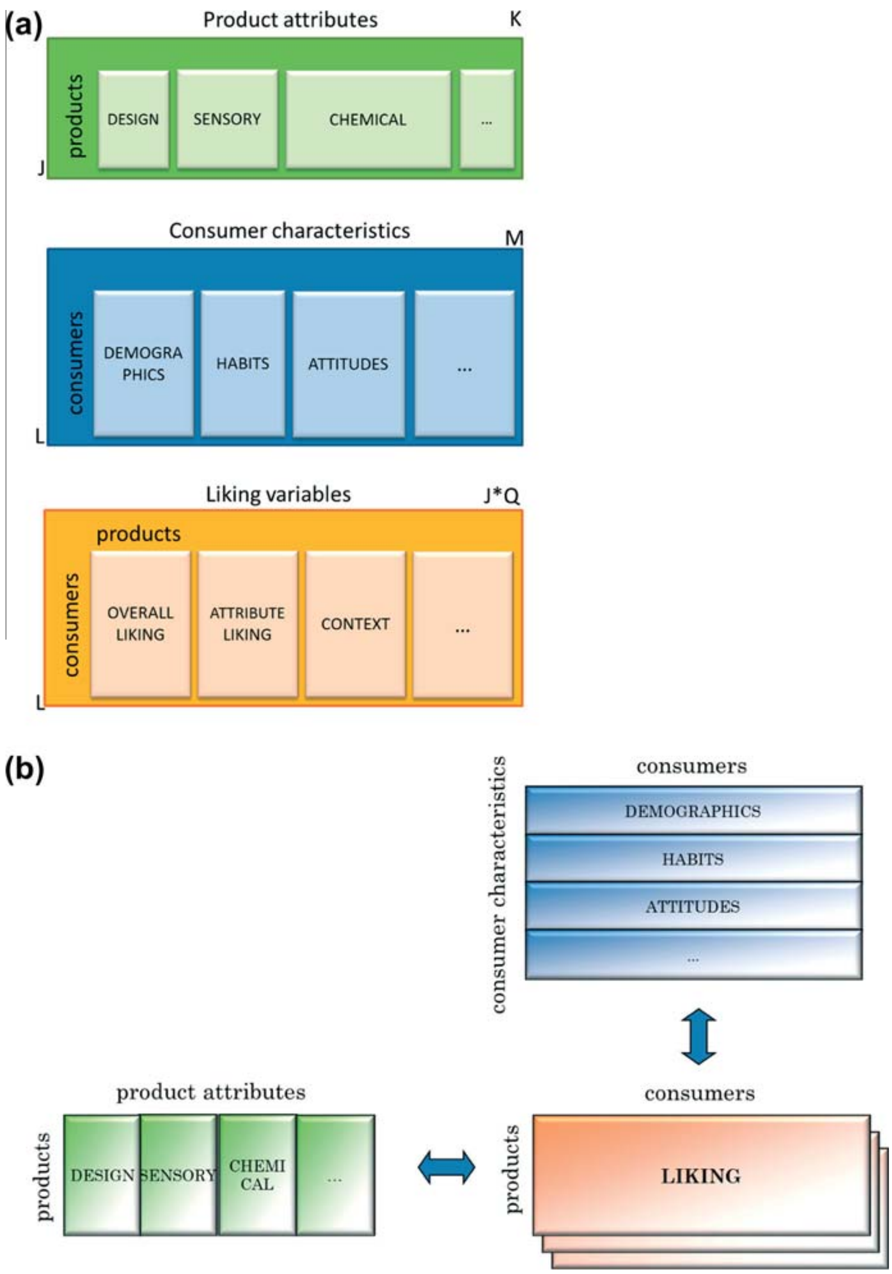

Fig. 1. The different types of data sets available (a) and their relations (b). The primary data consists of information about *J* products, related to design, sensory or chemical attributes, resulting in a data set of dimension J times *K*. The second data set consists of *M* consumer characteristics for each of the *L* consumers, related to demographics, attitudes and/or habits. The third data set is formed by acceptance values for each of the *L* consumers for each of the *J* products. This data set can include *Q* types of acceptance data, expressing overall impression, specific sensory attributes, eating contexts or meal combinations.

For the purpose of this paper, only the relevant aspects for illustrating the proposed methodology will be covered (see below and Table 1).

2.1.3. Organisation of the data blocks

The design can in this case be represented by one design variable with a number of levels corresponding to the number of products (equal to 3). In regression it is, however, better to represent it by three dummy variables (i.e. variables created by recording categorical variables, with more than one level, into a series of binary variables), one for each level. In order to avoid collinearity after centring, the last level is eliminated (in this case the level corresponding to chocolate 3). Product effects are therefore interpreted as differences from the reference level of chocolate number 3. The acceptance data is represented by overall liking scores of each consumer for each of the 3 tested chocolates.

As indicated above, the consumer characteristics data can sometimes be naturally split into blocks of data with a structure among them. How to decompose the data will depend on the specific situation, the problem to be addressed and the collected information available. In this paper we will consider the following consumer characteristics blocks, to be discussed next:

- In our example, gender and age information is available for each consumer, thus two different demographic blocks of data are created. In this case the age variable will be organized as a dichotomous (i.e. binary) variable with two levels (20–40 and

Table 1
The subscale from the "Attitude to chocolate questionnaire" (Benton et al., 1998).

Craving	
Craving1	I eat chocolate to chear me up when i am down
Craving2	I usually find myself wanting chocolate during afternoon
Craving3	Even when i do not really want any more chocolate i will often carry on eating it
Craving4	I often go into a shop for something else and end up buying chocolate
Craving5	I like to indulge in chocolate
Guilt	
Guilt1	I consider chocolate to be high in fat to be of pure nutrition value
Guilt2	After eating chocolate i often wish I had not
Guilt3	I feal unhealthy after I have eaten chocolate
Guilt4	I always look at the calorific value of a chocolate snack before I eat it
Guilt5	If I resist the temptation to eat chocolate i feel more in country of my life

40–60). For both gender and age, one level is eliminated for the purpose of avoiding collinearity problems. Each demographic block can thus be represented by one dummy variable. For the gender block, the value 1 is used for females and 0 for males. For the age block, the range 20–40 is coded by 1 and the range 40–60 by 0. Alternatively, one can include both variables into one single block.

- Attitude variables: the questionnaire statements considered in this paper are divided into two groups. The first group, represented by 5 statements, can be labeled "craving" and is associated with "preoccupation with chocolate", "weakness for chocolate when under emotional stress", and chocolate as a source of distraction (Benton et al., 1998). The second group, labeled "guilt", includes 5 statements that associate chocolate with negative experiences related to weight and body shape (Benton et al., 1998). Thus two attitude blocks are considered, each of five variables (see Table 1).

Based on the above, in our case of study $J = 3$, $K = 2$, $L = 248$, $M = 12$ (1 + 1 + 5 + 5). We will be interested in the inner relations between the four blocks of consumer characteristics as well as their relation to the liking values.

In this paper we will primarily consider two different structures of the data blocks. For both situations there will a description of how to organize the data for the path model calculations and also a description of how to relate the different blocks to each other, i.e. how the paths between the blocks are set up. Both situations will be discussed separately and in more details when comes to description of the methodological approaches in Section 3.

2.2. Partial Least Squares regression

Since the relations between the two vertically linked blocks in Fig. 1b are usually analyzed by regression and in particular PLS regression (Wold, Martens, & Wold, 1983; Wold, Sjöström, & Eriksson, 2001), this method will here be used as reference method to be compared with the path modelling approaches (Section 4). The main difference lies in the fact that for PLS regression all consumer characteristics are considered together in one single regression equation. It should, however, be mentioned that such analyses between different blocks could in principle be undertaken separately, if wanted, after the full regression of the main relation. Note that such an approach would resemble the SO-PLS approach taken in Næs et al. (2011)).

The PLS-2 regression relates two groups of variables, one considered as predictor and the other one as response, in order to describe their common structure. Specifically, in this case the method predicts the $L * J$ liking matrix, where the J columns represent the products and the L rows represent the consumers, from an $L * M$ matrix formed by the values of M consumer characteristics measured. This corresponds to a downward direction in the vertically linked relation in Fig. 1b.

2.3. Partial least squares path modelling

2.3.1. The PLS-PM theory

Although different methods can be used for analysing a path model, only the PLS-PM will here be considered. The comments given below about what type of information that can be extracted from the different structural approaches are general and hold equally well for other methods of estimation.

PLS-PM (Wold, 1979, 1985; Wold et al., 1983) is an iterative algorithm that estimates the relationships among blocks of observed variables (manifest variables: MV) through the construction of so-called latent variables (LV). These relationships form a system of interdependent equations based on simple and multiple regressions (Betzin & Henseler, 2005; McDonald, 1996; Vinzi et al., 2010). It can thus be considered an extension of the PLS/PCR regression methods (Næs & Martens, 1988; Wold et al., 1983).

2.3.1.1. Model. The PLS-PM comprises two models closely linked: a measurement model, explaining the relations between the manifest variables of the different blocks and their latent variable, and a structural model, relating the latent variables in the different blocks to other latent variables (Tenenhaus et al., 2005). In all models to be considered here, the variables are mean-centred.

In the measurement model, a manifest variable x_{pq} can be related to its own latent variable ξ_q in three ways or modes (Tenenhaus et al., 2005), depending on the direction of the assumed relationships between the LV and the corresponding MVs. In the reflective way, the LV is assumed to be a common factor that describes its own MVs. The relation can be written as:

$$x_{pq} = \gamma_{p0} + \gamma_{pq}\xi_q + \varepsilon_{pq} \tag{1}$$

where γ_{pq} is the loading associated with the *pth* manifest variable in the *qth* block.

The formative mode assumes that the LV is generated by its own MVs, these representing different aspects of an underlying concept:

$$\xi_q = \sum_{p=1}^{p_q} w_{pq}x_{pq} + \delta_q \tag{2}$$

The MIMIC mode is a mixture of the previous two. It means that some MVs can follow a reflective way and the other ones follow a formative way. Whatever measurement model is used, the LV scores are estimated according the so-called weight relationship:

$$\hat{\xi}_q = \sum_{p=1}^{p_q} w_{pq}x_{pq} \tag{3}$$

where w_{pq} are the outer weights. The weight relationship only implies that any LV is defined as a weighted sum of its own MV and does not affect the direction of the relation between LV and MVs.

Finally the model that accounts for the relationships among the LVs (structural model) is expressed by:

$$\xi_j = \beta_{0j} + \sum_q \beta qj \xi_q + \zeta_j \tag{4}$$

where ξ_j is the generic dependent latent variable, β_{qj} is the path coefficient relating the *qth* independent latent variable to the *jth* dependent one, and ζ_j is the random error.

The description above is based on the same notation as in Vinzi et al. (2010). We refer to Tenenhaus et al. (2005) and Vinzi et al. (2010) for an exhaustive explanation of the PLS-PM methodology. Note that this classical setup essentially assumes the unidimensionality of the (reflective) blocks, i.e. the first eigenvalue is dominating completely over the rest, which will also be discussed below.

2.3.1.2. Estimation. The estimates of weights and LV scores are achieved through an iterative procedure consisting of outer (measurement model) and inner (structural model) estimations. The choice of the outer weight estimation model is strictly related to the nature of the measurement model assumed. The so-called Mode A is used for the reflective blocks and the so-called Mode B is used for formative blocks. If the manifest variables in a formative block are collinear, the so-called PLS Mode can be used (Vinzi et al., 2010). For estimation of the inner relations, three different options are available (Wold, 1985). In this paper we will follow the recommendation by Vinzi et al. (2010) of using the path weighting scheme, since it is the only option that accounts for the direction of the links in the structural model. More precisely, if the outer estimate of the qth LV (i.e. the linear combination of its own MVs) is the dependent variable in the structural equation, then the inner weight is equal to the regression coefficient between the outer estimate of the qth LV and the outer estimate of the LV that is connected with it; if the outer estimate of the qth LV plays instead the role of predictor in the structural equation, the inner weight equals the correlation coefficient (Vinzi & Russolillo, 2013; Vinzi et al., 2010). After convergence the structural equations are usually estimated by individual OLS multiple regressions. In case of multicollinearity between the estimated LVs, the OLS estimations may be disturbed and thus PLS regression is applied instead. In our situation, OLS is used.

The properties of the estimates are in this paper estimated by the use of the non-parametric bootstrap procedure, see XLSTAT (Addinsoft., 2012). For further discussion of statistical properties, optimization criterion and convergence properties we refer to Vinzi and Russolillo (2013) and Cassel and colleagues (Cassel, Hackl, & Westlund, 1999, 2000).

2.3.2. Considerations for consumer studies

2.3.2.1. Formative versus reflective mode. The distinction between the formative and reflective modes is important, since proper specification of a measurement model is necessary to assign meaningful relationships in the structural model (Anderson & Gerbin, 1988). Researchers in various disciplines have undertaken studies to reveal consequences of misspecification (Diamantopoulos & Siguaw, 2006; Law & Wong, 1999; MacKenzie, Podsakoff, & Jarvis, 2005) and to develop guidelines for a proper choice.

In a consumer study with different blocks representing different types of consumer characteristics, product attributes and liking variables, the choice of the proper modes is not obvious. In light of previous research (Bech et al., 2000; Coltman, Devinney, Midgley, & Venaik, 2008; Diamantopoulos & Siguaw, 2006; Tenenhaus et al., 2005) it is generally most appropriate to model sensory variables and also possibly habits/attitudes variables as reflective blocks. The reasons is that sensory data can naturally be considered as functions of an underlying sensory space, and attitude scales are often developed with an underlying uni-dimensional concept in mind (Bollen & Lennox, 1991; Diamantopoulos & Siguaw, 2006). Similar considerations are made for the liking data. In the reflective mode the variables should have high intercorrelations in order to satisfy the requirement of uni-dimensionality. In our example there is no sensory information and the considered attitudes' blocks have already been shown to reflect one-dimensional concepts from factor analysis (Benton et al., 1998). More careful considerations will be made below for the liking data, in relation to each of the considered approaches.

In principle, the one-dimensionality of the reflective block should be checked. If a reflective block has more than one underlying dimension, a possibility is to model the block as a formative block and use the PLS mode mentioned above instead. This is not fully satisfactory, but can be considered a reasonable and pragmatic approach. Research has recently been done to relax on this assumption in a path modelling context (Næs et al., 2011). Another possible approach is to split the block in one-dimensional sub-blocks. The latter will be considered in this paper, in particular for the liking data, as explained below (Section 3.2).

For design variables and demographic variables, the formative mode is the most natural since they cannot easily be considered as functions of underlying latent variables. The latent design and demographic variables are thus not assumed to be one-dimensional, i.e. each manifest variable represents a different dimension of the underlying concept. This choice is also justified by well-defined concepts for the blocks, interpreted through simple meanings or calculations (Coltman et al., 2008). Formative variables can possess either high/low, positive/negative or no intercorrelation (Coltman et al., 2008).

2.3.2.2. Pre-processing. In compliance with the path modelling literature (Lohmöller, 1989), when the scales of the MVs are not comparable, all variables are standardized, i.e. divided by their standard deviation. This is the case for a consumer study with dummy variables and sensory, liking and consumer characteristics variables measured on different types of scales.

Some additional pre-processing strategies can sometimes be useful, in addition to the mean-centring which is always done. If the consumer acceptance data or the consumer characteristics data have a component related to a different use of the scale, it may be wise to subtract the mean from each consumer prior to path modelling, as is done in for instance preference mapping. In this way the first components will not be mainly related to the "up-down movement" on the scale due to different centering of the scores for each of the consumers (Næs et al., 2010b).

In some cases it may also be useful to centre liking data in the other direction (Endrizzi et al., 2011), i.e. for each consumer across the products tested. If already centered for each consumer, then the data set becomes double centered. The effect of double mean centering is that one considers each consumer's position relative to the other consumers for each of the products. In other words, the double centering leads to an analysis of the relative differences between the consumers in their assessment of the different products, after the product effect has been eliminated. In our example we will investigate also this possibility. We refer to Endrizzi et al. (2011) for further discussion on double centring.

It is worth mentioning that for both the regular PLS results and the results for approach 2 below, the data will automatically be double centred, since the "variables" in these cases correspond to the liking for the different products and both methods centre vertically before modelling. For the approach 1, centring for each consumer makes no sense since this will per definition eliminate the main effects of the consumer attributes on the liking (see also below).

2.3.2.3. Further considerations. It should be mentioned that generally the relations between consumer characteristics and liking pattern may be quite weak (Næs et al., 2010b). Therefore, the type of relations that will be considered in this paper can seldom be used for any meaningful predictions, but only for estimating tendencies in the population. In this paper main emphasis is thus put on interpretation based on plots and regression coefficients assessed by the bootstrap.

3. Methodological approaches

The approaches presented in this paper have the aim of investigating the relationships among the blocks of different consumer characteristics and between these and the individual liking. Both the products and the consumer characteristics blocks will be related to the liking. One of the main challenges is thus how to organise the data matrices prior to analysis. As can be seen in Fig. 1a, the different data blocks have different dimensionalities and it is not obvious how to combine them. In the following, we will thus discuss two different approaches, the relation between them and how they relate to other methodologies.

The major difference between the two approaches is what is defined as "variables" and what is defined as "objects" in the data sets. This will lead to different path models. The way the different features of the set of consumer characteristics are related to each other will, however, be the same. We will in all cases assume that all the blocks of consumer characteristics can influence the liking, that both gender and age may influence craving and guilt and moreover that craving may have an influence on guilt (Benton et al., 1998). The blocks are thus related according to what is considered natural and what is of interest to study. No attempts versus claiming causal relations or effects will here be made.

3.1. Approach 1

3.1.1. Structure

For this approach (Fig. 2) the liking block includes one single variable of length $L*J$, with L being the consumers and J being any number of available products. This means that the liking scores matrix is unfolded in the vertical direction, thus the block is unidimensional by construction. If more than one liking variable is available, Q blocks are considered as separate blocks of dependent variables. The consumer and product data are organized accordingly. For the consumer characteristics' blocks each response for each consumer is repeated J times. The product data are likewise organized as an $L*J$ times K matrix, with the K product variables (consisting of J rows) repeated L times. It is also possible to incorporate interactions between the product design variables in the same block. As can be seen, this structure resembles the one used in the simultaneous ANOVA of conjoint variables and consumer characteristics discussed in Næs et al. (2010b). The difference is that in this case the consumer characteristics are divided into blocks according to their nature (Fig. 1). The different blocks depicted in Fig. 2 will be related according to the path model presented in Fig. 3.a. As can be seen, all blocks are related to liking and some of the blocks also have a path relation to each other, as described above.

3.1.2. Interpretation

When PLS-PM is used for the structure in Fig. 2, the essential information in the regression coefficients (if only regular centering for each variable separately is used) is information about average effects in the population of both the product attributes and the consumer characteristics. For the former (products) this is natural, but for the latter (consumers) this is less so, since this would mean that a consumer group has an average liking higher than another for all products. Usually, the important information is found in the interactions between product and consumer group. In order to obtain the consumer-product interactions in this case, it is necessary to add an extra block of product effects (products between product attributes and consumer characteristics), but this increases the complexity and it is often not obvious how to incorporate such an additional block in the path model.

As indicated above, the liking scores given by the different consumers may also be related to different ways of using the scale by the consumers (Endrizzi et al., 2011; Næs et al., 2010b; Romano, Brockhoff, Hersleth, Tomic, & Næs, 2008). In this case, however, consumer centering will eliminate the main effect relations (i.e. they become identical to 0) mentioned in the previous paragraph. The same will thus be true for double centered data. It is therefore not meaningful for this approach to use any of these alternatives.

3.2. Approach 2

3.2.1. Structure

The consumer characteristics data set, in this case, has dimension $L*M$, with as many rows as the number of consumers and with columns given by the M consumer characteristics (Fig. 4). The liking data can be organized in different ways. The first alternative is in a $L*J$ matrix, with L consumers as rows and J products as columns (Fig. 4), but only if the block is uni-dimensional (see Section 2.3). The second alternative is to have J response blocks, each one containing the liking or residual liking values of each consumer for the specific product, so that the uni-dimensionality is given by construction. The third alternative is to organize the liking data in A blocks (with A being usually equal to 2 or 3), related to the first A principal components from PCA of the liking or residual liking values. In the more general case with Q liking variables, these considerations are repeated Q times. Regardless of the alternative chosen, each consumer block will be linked to each of the liking blocks according to the assumed relations depicted for the second approach in Fig. 3b. As can be seen, the relations/paths between the consumer characteristics blocks are the same as for the previous approach (Fig. 3a).

3.2.2. Interpretation

This approach corresponds to the regression method in Næs et al. (2010b), using the liking of the products as Y and consumer characteristics as X. The difference is that in this case there are several blocks of consumer data that are linked to each other and to the response block(s) using a path modelling approach. It should also be mentioned that, if double centering is used for the product block, the setup is very similar to the one proposed in Endrizzi et al. (2011), again the main difference being related to path modelling vs. parallel analysis of the consumer characteristics.

The main advantage of this approach is that it does not focus on the average effect on liking for a consumer characteristic variable, but on the effect on the different products or principal components separately. Thus it focuses conceptually on the interactions between the consumer characteristics and the products. In other words, it takes into account that the different consumer groups can have a different liking pattern. This aspect is very important in practice, since this is expected to be more interesting and more frequently occurring than just a main effect, as was discussed for the first approach.

The possibility of using the principal components is particularly interesting in this context; first of all because it is quite general and can be used for a large number of products. In many cases, the preference space for even a quite large number of components will often be low-dimensional. Secondly, it is useful because one can often interpret the principal components in terms of the design variables involved. This can be done either visually or by ANOVA of the PCA loadings (for the products) versus the design variables, as was suggested in Endrizzi et al. (2011).

It is important to emphasise that, since this approach only focuses on differences in liking pattern, it is always necessary to add an ANOVA for analysing the main product effects.

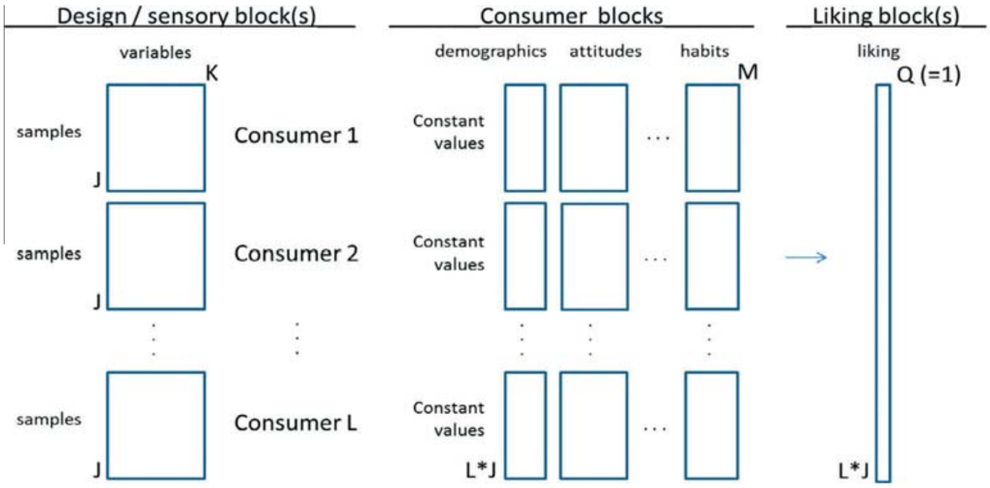

Fig. 2. A graphical illustration of how the data sets are organised for approach 1.

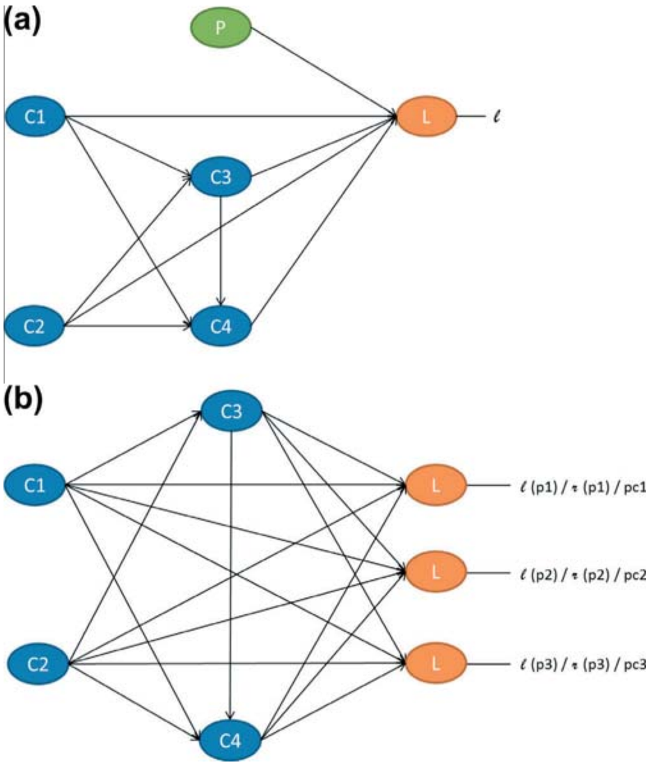

Fig. 3. Representative example of approach 1 (a) and approach 2 (b). In this representation four consumer characteristics blocks (C1, C2, C3, C4) are considered. In the paper C1 and C2 are demographics blocks (gender and age), C3 corresponds to craving and C4 to guilt. The product data, here related the three products (p1, p2, p3), are included into one block (P). One type of liking information (overall liking L) is available, represented as either liking values (l) or residual values (r) or again principal components (pc1, pc2, pc3) from PCA of the liking or residual values (see below).

4. Results

4.1. Regular ANOVA

The ANOVA for explaining the consumer liking using product effect and consumer effect has been performed. This is necessary when considering the second approach, since it does not focus on main effects but on interactions between products and consumer characteristics. In addition, the residuals of this model, corresponding to the double centered values, can directly be used in the liking blocks when exploring individual differences is of interest (see the pre-processing paragraph in Section 2.3.2). For the first approach this analysis should be used when double centering, since the product main effects are not available. Anyway, as already discussed (Section 3.1.2), this pre-processing strategy makes here no sense.

Results (Table 2) show that both product and consumer factors are significant. According to the grouping information, using Tukey method and 95% confidence, the means of the three products are significantly different one from each other with respect to liking. The most liked chocolate is product 1 (well known in the market), followed by the new powerful and rich chocolate (product 3) and lastly by the new sweet and cocoa taste chocolate (product 2).

4.2. Regular PLS regression

PLS regression has also been run as a reference analysis to be compared with the two path modelling approaches (Section 4.3.3). The considered structure of the data set is the one adopted in approach 2, with the liking for the different products as separate columns. The liking variables are consumer centered, as done in both the proposed approaches. Note that with the setup used here, the liking data are double centered (see also above). Since different scales were used, the variables have also been standardized.

As can be seen from the loadings in Fig. 5a, all the craving variables are located to the left along the first component, while the guilt variables have a contribution in both the components. The direction of the age variable seems to indicate that young consumers are positively related to almost all the craving variables. Looking at the third component as well (Fig. 5b), there is a tendency, although very weak, of a positive relation between the gender variable (i.e. female consumers) and both craving and guilt. The liking for product 3 is in the direction of the age and craving variables, which could indicate that young consumers that crave for chocolate prefer this product. It seems instead negatively related to a guilt variable (Guilt 5, see Table 1). The opposite seems to be true for the liking of chocolate 1 (i.e. opposite signs of the relevant regression coefficients). The liking of product 2 is related positively with most of the guilt statements and negatively with craving statements and age.

The scores plot (Fig. 5c) shows only that there is a large disagreement among consumers; anyway it seems that the majority lies on the upper side of the plot, in direction of product 1, and

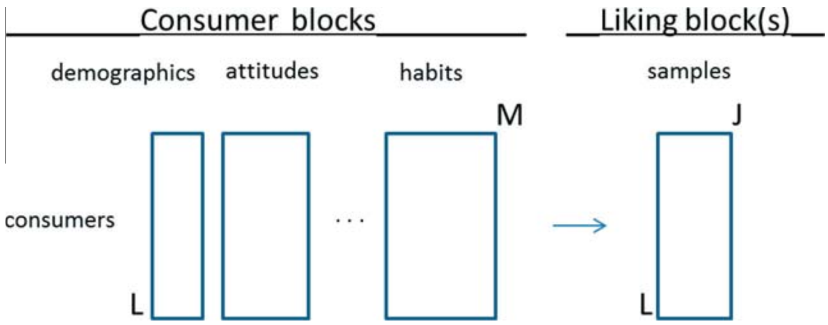

Fig. 4. A graphical illustration of how the data sets are organised for approach 2. The liking data can here be organized in a $L * J$ matrix only if the block is uni-dimensional. If not so, alternatives are possible (Section 3.2.1).

Table 2
Results from ANOVA of the chocolate data: *P*-values for product and consumer factors and means for the liking of each product. According to the grouping information (using Tukey method and 95% confidence), the means that do not share a letter are significantly different. The residuals of this model are used for exploring individual differences (see the pre-processing paragraph in Section 2.2.1).

Effect	*P*-value	Mean [Grouping]		
		p1	p2	p3
Product	<0.001			
Consumer	<0.001	7.238 [A]	5.976 [B]	6.532 [C]

on the left- hand side towards product 3, in agreement with the ANOVA results (Table 2).

A study of possible outliers was conducted (scores and residuals), but no serious outliers were found.

4.3. The two approaches for organising the data for SEM

In the following, the chosen significance level for the relations between blocks is 0.1. In the figures the significant relations are displayed by thick arrows, the other arrows are shown in a lighter font. Regression coefficients and significance values (assessed by bootstrap) are indicated only for the significant relations. The correlation coefficients between MVs and their own LVs are indicated only if different from 1.

The uni-dimensionality of the age and gender blocks is given by construction. For the guilt and craving blocks, this assumption has been checked by PCA (not shown) and is satisfied. For the liking block(s), the considerations made in Sections 3.1.1 and 3.2.1 are followed.

4.3.1. Approach 1

The results from the first approach (Fig. 6) indicate that all the relations between the consumer characteristics blocks are significant. In particular, women and young consumers have a stronger tendency towards chocolate craving and guilt, since the regression coefficients are positive in both cases. Furthermore, the higher value of craving, the higher value of guilt. The design block is significantly and strongly related to the liking block, meaning that the product information dominate the acceptance patterns. Product 1 has a high and positive correlation with the design latent variable, the opposite being true for product 2. This means that, on average, the chocolate which is the market leader is the most liked one by the population of consumers and that product 2 is liked less than the reference product 3. This corresponds well to the mean liking for each product (Table 2) and to the PLS regression results. The consumer characteristics blocks are not significantly linked to the liking but the age block. This means that consumers under 40 years old seem to use mostly the lower part of the 9-point hedonic scale (i.e. scale effect because of the not consumer-centered data) for expressing their liking. Note that, as was discussed above, mean centering for each consumer makes no sense here.

As can thus be concluded, this approach was useful for estimating average product effects on the liking. The relations between the consumer characteristics blocks were significant and clear for this method.

4.3.2. Approach 2

Since the $L * J$ liking matrix is not uni-dimensional, the following path models (along the line discussed in section 3.2.1) are created. First we organize the liking data in (i) three blocks, each representing the consumer-centered liking values for a specific product. Then we create (ii) two blocks related to the first two principal components from PCA of the centered liking values.

From all models described below it is evident that all the consumer characteristics blocks have strongly significant relations between each other (with the exception of a not significant link between age and guilt), confirming the results from approach 1. Thus women seem to be more prone to chocolate cravings and have more guilt feelings when eating chocolate than men. Furthermore the more a consumer craves for chocolate, the more he/she feels guilty and unhealthy after consumption.

The importance of interactions between consumer characteristics and product information for explaining the liking can be highlighted in various ways. When considering model (i) (Fig. 7), focus is on the differences in liking between the actual products. In particular, from the results one can see that the more one craves for chocolate, the more one significantly likes product 3. A possible explanation is that this product has been described as a powerful and rich chocolate (in correspondence to its sensory properties, see Section 2.1.2), giving the impression of being the fattest. The liking relations with the other two products are opposite to product 3 but anyway not significant.

The alternative (ii) requires a preliminary interpretation of the two principal components from the PCA of the consumer centered liking values (i.e. internal preference mapping). As one can see in Fig. 8, the first component differentiates the market leader product (product 1 is extreme on the positive x-axis) from the two new chocolates (negative x-values). The second component is contrasting the products 2 and 3, with product 1 in the middle. The path modelling results (Fig. 9) indicate that there is only a significant effect related to the second component. On average, consumers clearly discriminate between the two new products, in particular in connection to craving attitudes. When consumers crave for chocolate, they like product 3 more than product 2. Furthermore, the age block is close to be significant with a positive effect on the second liking block. This means that the young consumers tend to have a higher acceptance for the rich and powerful chocolate

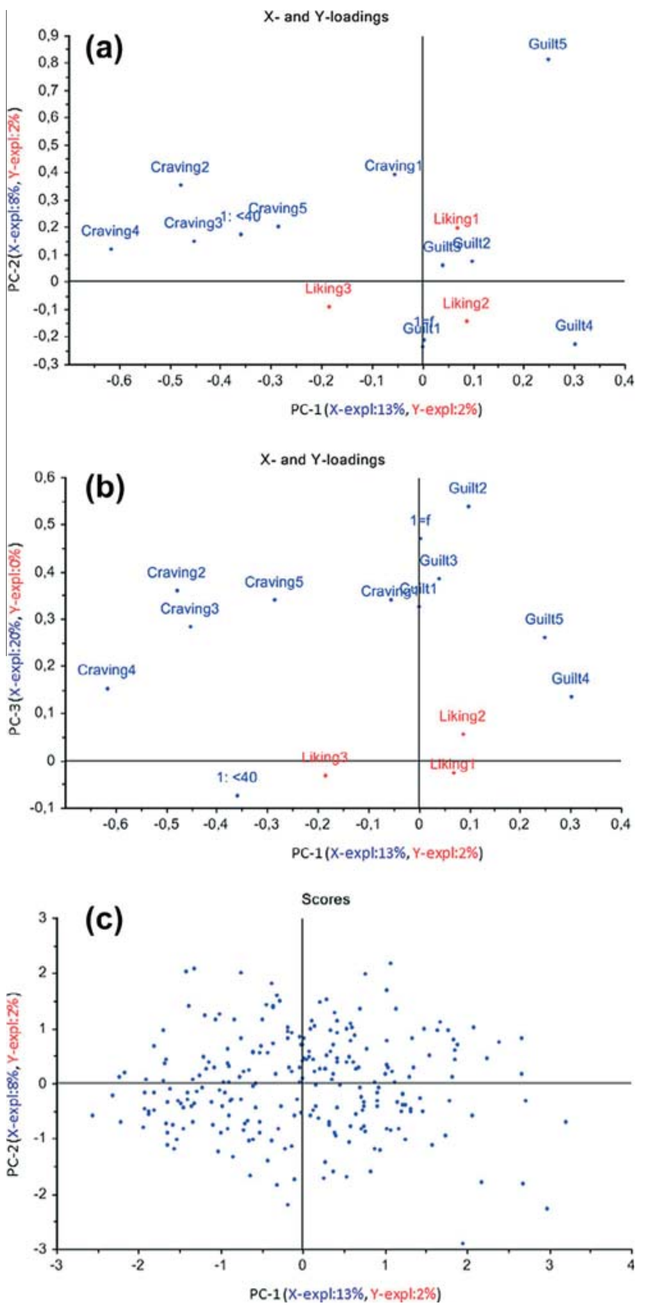

Fig. 5. Loadings plots for the first two components (a) and for the first and third component (b) and scores plot for the first two components (c) from a regular PLS regression of the consumer characteristics (X) versus the liking variables (Y). Data have been structured in a similar way as in Fig. 4.

(product 3) than product 2 (described as having a clear cacao taste and great sweetness, but not as fat as product 3).

Indirect effects should finally be highlighted. The effect of a latent variable (independent) on another variable (dependent) through a third one (mediator) is calculated as the product of the direct paths involved, i.e. the product of the regression coefficients between the independent variable and the mediator variable and between the mediator variable and the dependent variable. A list of all the indirect effects is given in Table 3, along with the standard errors and the bounds of confidence intervals, but only the significant effects are described here. Results show that gender (coefficient = 0.072) and age (coefficient = 0.053) have a positive effect on guilt through craving, meaning that those women and young consumers that tend to crave for chocolate will feel guiltier than the other consumers. There is no significant indirect effect of craving on the liking.

The outliers analysis has here been done using PLS regression for estimating the path coefficients (not shown). Also in this case, the results were satisfactory.

It should be mentioned that the PCA is here used only as a way of visualizing differences between products and also that this approach is even more useful when comes to situations with a higher number of products. It should also be mentioned that in this second approach the consumers may not be 100% centered since only the first principal components, explaining most of the variability, are used.

Note that the ANOVA is here absolutely necessary in both approaches for analyzing the average product effects.

4.3.3. Comparison with standard PLS regression

There are many similarities between the results from regular PLS regression and those obtained by the PLS-PM approach 2 (i.e. the approach with a similar data structure). Age is positively correlated to craving and not to guilt (approach 1 gave also a significant positive relation between age and guilt). Also the significant relation between craving and the liking for product 3 is highlighted in both cases. In any case, the PLS regression does not make the relation between the consumer variables as clear as for the PM approach. For PLS regression it is not possible to understand the relations between guilt and the other variables, since the guilt variables are absorbed into different dimensions (mainly the second and third components). Direct relations (for example the one between craving and guilt) are not so easy to see, since inter-correlated variables are in the standard PLS regression considered individually and in parallel with all the other explanatory variables. Moreover there is no information about direct, indirect and total effects in the regression approach. For example, with respect to age, it is not possible to clearly detect its direct effect on craving and its indirect effect on guilt through craving. The same is true for the relations between the consumer characteristics and the liking variables (in this example only not significant indirect effects on the liking blocks are present). The total effects can be calculated as the sum of the direct and indirect effects for the respective blocks.

5. Discussion

5.1. Comparison of the two structural approaches

As can be seen from the empirical results, the two approaches have different focus, clarity and strength, but give comparable results for those aspects that are possible to compare. Approach 1 focuses on the overall effect of the blocks of consumer variables as well as the design on the liking. In practice, however, it is not always likely that a consumer group has a liking that is systematically above or below the average for all products, even though it may happen. If the data are centred for each consumer this effect is not available. A more interesting aspect to consider is linked to the interactions between the consumer characteristics and the products, i.e. how the different groups perceive differences between the products. This is in ANOVA accomplished by adding interactions between product attributes and consumer characteristics (see e.g. Næs et al. (2010b)), but in path modelling using approach 1 this is more difficult. A possibility is to add a block consisting of the products of variables, but this clearly adds to the complexity and it is not obvious how to link such a block to the others. Approach 2 on the other hand focuses directly on these interactions. The reason for this is that each consumer characteristic will have a separate effect for each of the products, i.e.

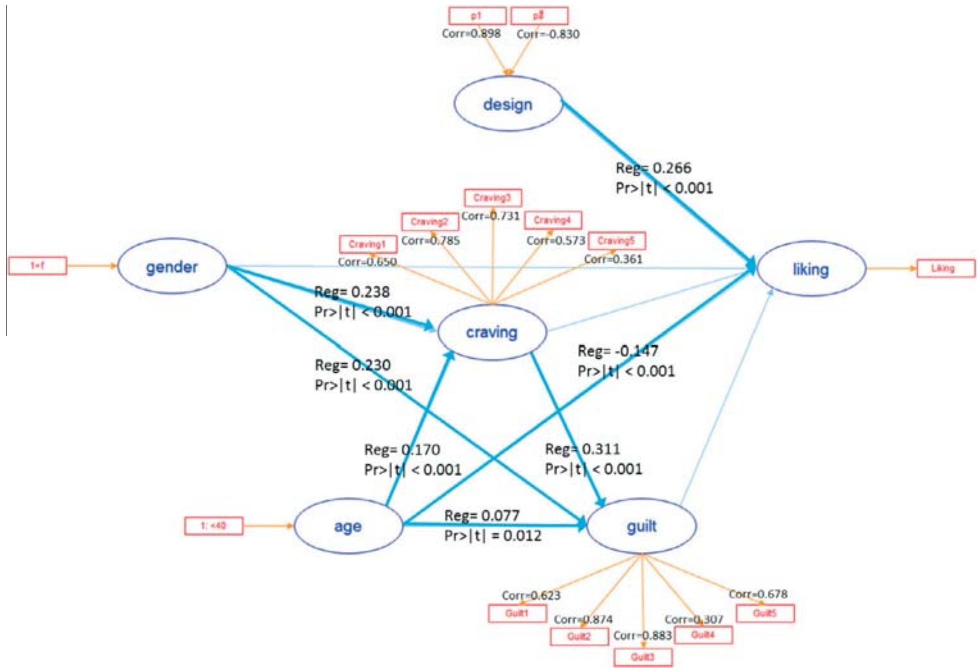

Fig. 6. Results for approach 1, according to the data structure in Fig. 2. Focus is on average effects in the populations, for both product effects and consumer characteristics. Only the significant relations are highlighted (the chosen significance level is 0.1).

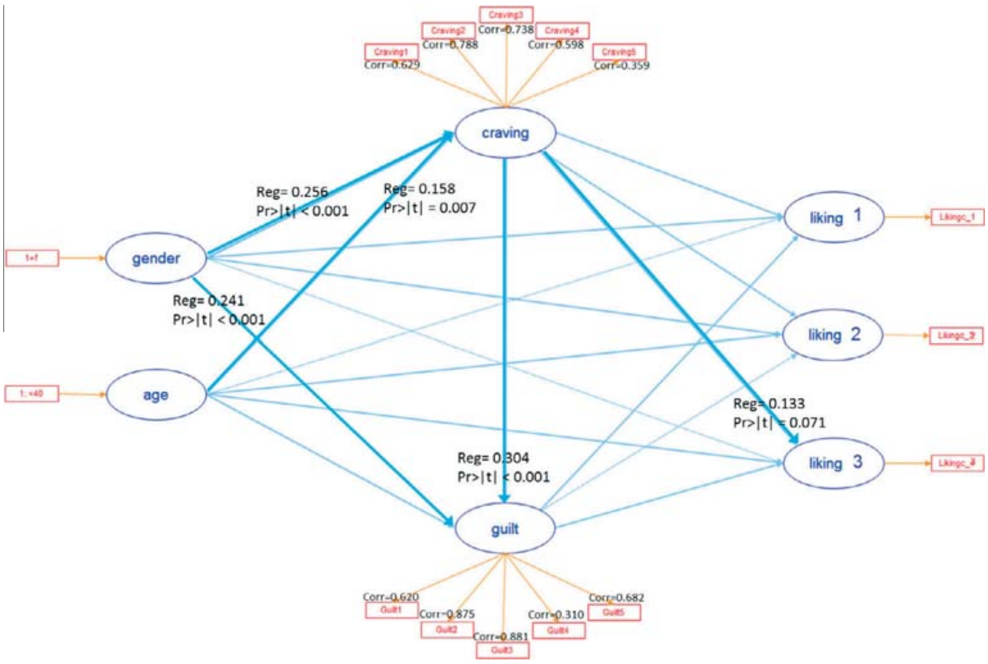

Fig. 7. Results for approach 2, according to the data structure in Fig. 4. The manifest variables in the liking blocks consist of the consumer centred liking values for each product. Focus is on interactions between the consumer attributes and the products. Only the significant relations are highlighted (the chosen significance level is 0.1).

each of the columns in the dependent liking block (see Fig. 4). In this way one can get specific and detailed information about how each consumer characteristic is related to each of the products. If the principal components are used instead, the same is true, but now for the components and not for the individual products. Since the second approach focuses only on differences in liking pattern, the ANOVA is required for analysing the main product effects.

5.2. Relations between a SEM and a regression approach

The main difference between a regression and a SEM approach, as already mentioned, is that the consumer characteristics are for the latter organized in blocks, with each block being a collection of related characteristics. This means that it is possible to link the consumer blocks to each other and to the liking blocks, allowing for estimation of both direct (i.e. the path coefficients)

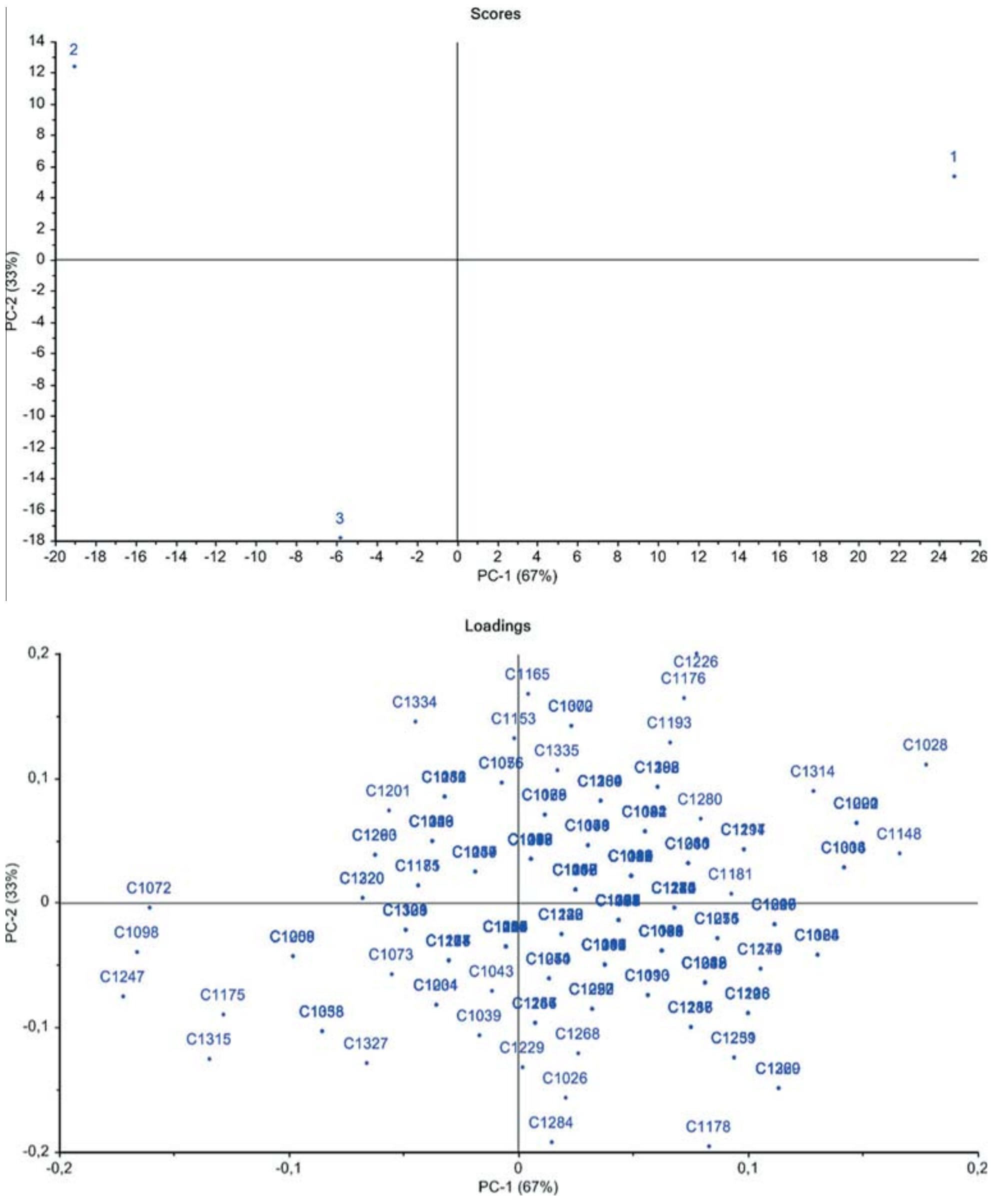

Fig. 8. PCA of the consumer centred liking values (internal preference mapping). The first two principal components are used for the two liking blocks in the alternative (ii) for the second approach (see Section 4.3.2).

and indirect effects (i.e. effect that a latent variable may have through other latent variables) (Bollen, 1987, 1989).

The regression on the other hand considers all the explanatory variables in a parallel way, thus it does not provide a direct measure of the relations among them. Interpreting PLS loadings plots may give an idea of the relations between consumer variables through the variables' proximity in the space, but this is difficult when there are many variables with possibly strong inter-correlation between them. In addition, variables from one single block may be absorbed into different dimensions.

5.3. Pre-processing

As indicated in Section 2.3.2, the pre-processing is a fundamental step for all the approaches described in this paper. Centering and standardization should always be done in such studies, since different scales are used for the different variables and since the methods are not scale invariant. Subtracting the mean for each consumer is also an important possibility if one expects this effect to be more related to the use of the scale than to information about individual differences (see for instance preference mapping studies).

As was noted above, the PLS regression and approach 2 automatically use double centered dependent variables if consumer centering is used. For the approach 1, however, consumer centering makes no sense. The interpretation of the difference between the double centred and the original values is mentioned in Section 2.3.2 and can be found in Endrizzi et al. (2011). In general one can say that the double centred approach focuses solely on the relative individual differences, while the original data are more focused on differences in liking of the products.

5.4. Possible extensions

As already mentioned, the whole discussion in this paper is driven by the organisation of data and interpretation of the relations

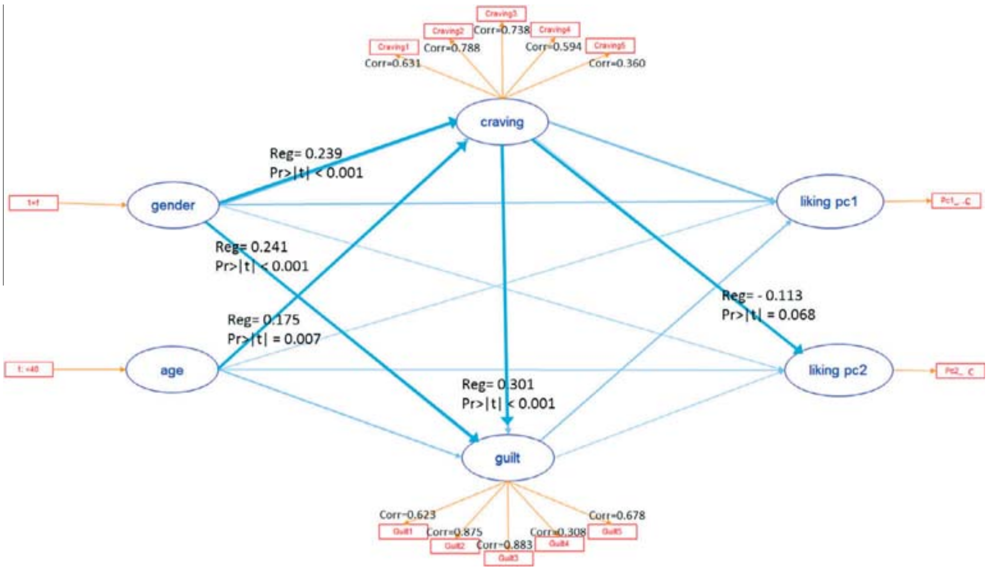

Fig. 9. Results for approach 2, according to the data structure in Fig. 4. The manifest variables in the liking blocks are the principal components from PCA of the consumer centred liking values (Fig. 8). Focus is on interactions between the consumer attributes and the PCA components. Only the significant relations are highlighted (the chosen significance level is 0.1).

Table 3
Indirect effects between latent variables, for the PLS-PM according to approach 2 and with the manifest variables in the liking blocks being the principal components from PCA of the consumer centred liking values (Fig. 8). The coefficients and standard errors are assessed by bootstrap, the bounds of confidence intervals are at 90% confidence level.

From	To	Effects	Standard error	Lower bound	Upper bound
Gender	Guilt	0.072	0.027	0.029	0.124
Age	Guilt	0.053	0.025	0.014	0.107
Gender	PC1	0.001	0.028	−0.039	0.046
Age	PC1	0.000	0.016	−0.032	0.026
Craving	PC1	0.002	0.022	−0.035	0.038
Gender	PC2	−0.003	0.024	−0.043	0.039
Age	PC2	−0.010	0.018	−0.041	0.012
Craving	PC2	0.021	0.023	−0.018	0.061

and not by which estimation method is used. It should also be mentioned that many other path modeling methodologies are available (Høskuldsson, 2008; Jöreskog, 1978; Jöreskog & Sörbom, 1989; Næs et al., 2011; Tenenhaus & Tenenhaus, 2011; Vinzi, 2009), each one with a particular focus, different assumptions and properties. The PLS-PM chosen here is an approach that has good properties with respect to convergence (Hanafi, 2007; Henseler, 2010) and it can be used also for situations with strong collinearities. As such it is quite simple to apply, using for instance the XLSTAT software (Addinsoft, 2012). The statistical properties are, however, not fully developed yet (Cassel et al., 1999, 2000) and we have therefore chosen a non-parametric approach based on the bootstrap for estimating standard deviations and p-values for the estimates. Another possible approach, which should also be investigated within this framework, is the LISREL approach (Jöreskog, 1978; Jöreskog & Sörbom, 1989). A third possibility is to use the newly developed SO-PLS (Næs et al., 2011) which is based on sequential use of PLS regression and orthogonalisation. The approach is invariant to the relative scale of the blocks, it handles collinear data and it can allow for multi-dimensional blocks. Yet another possibility, that can be of some interest in this context, is the PO-PLS method which looks for common and unique components among several blocks (Måge, Menichelli, & Næs, 2012; Måge, Mevik, & Næs, 2008). Since the main focus of this paper is on the structural aspect of how to combine data, it is beyond the scope of the present paper to consider these methods. Work is in progress for evaluating the possibility of using the SO-PLS method in this context.

As depicted in Fig. 1, the product data can include design variables, sensory (or chemical) attributes and/ or both of them. The proposed approaches can thus be applied to both preference mapping and conjoint studies. In the conjoint case, the product block(s) will consist of design variables (or a number of dummy variables related to the number of levels for each design variable, as done in the present paper). In preference mapping the corresponding data block consists of the sensory properties of the products. This means that in Fig. 1b the horizontal link will correspond to the standard preference mapping link between sensory properties and consumer liking (Næs et al., 2010). In this case the reflective mode for the measurement model should be chosen (see Section 2.3.2) and thus the unidimensionality needs to be checked. If this assumption is not satisfied for the sensory block, a possibility is to split this block in one-dimensional sub-blocks according to the different sensory modalities (Måge et al., 2012). Situations with both a design block and a sensory block are also possible. We refer to Menichelli et al. (2012) for an example of this and a discussion of how to set up such experiments. It should also be mentioned that the proposed methodology can possibly also be extended to include other types of liking data (choice or ranking data). One possibility is to reshape or recode the liking or preference data into dummy variables or estimated individual regression coefficients, as obtained by using for instance a mixed logit approach (Campbell, 2007; Train, 2009).

6. Conclusions

In this paper two different approaches based on PLS-PM have been investigated, for the purpose of relating different blocks of consumers' characteristics to each other and to consumer acceptance, when product information (i.e. design, sensory or chemical data) is also available. The first approach focuses on the overall effects on liking of consumer characteristics and product variables, while the second approach focuses conceptually on the interactions between the consumer characteristics and the products. The latter is recommended in consumer studies of this type: this has been shown to give not only a deep insight into the relations between different types of consumer variables, but also interpretative advantages in understanding the acceptance patterns, since it takes into account that different consumer groups can have a different liking for the different products.

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Paper V

The SO-PLS approach to Path Modelling in consumer science

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Abstract
This paper presents the new path modelling approach by Sequential Orthogonalised PLS regression within the context of consumer science. The method is based on splitting the process into a sequence of modelling steps for each dependent block versus its predictive blocks. Focus will be on how the method can be used to combine individual variables or specific groups of variables in more general blocks with a broader interpretation, such as for instance consumer habits, attitudes and demographic variables. It will be explored how the method handles multidimensionality of the blocks and thus how the analysis is simplified, at least for explorative purposes, as compared to other more traditional path modelling approaches. An application based on a consumer test on iced-coffees will be used as illustration. The study shows that important relations are revealed in presence of different types of information like product attributes, consumer characteristics and acceptance.

Keywords
Path modelling; SO-PLS; orthogonalisation; regression; multi-block.

1. Introduction
In modern science there is often a strong need to understand the relations between several large and complex data sets, so-called multi-block data sets. The relations between data blocks, with a block being a collection of related variables, can have a predictive direction (Bollen, 1989; Høskuldsson, 2008; Måge, Menichelli, & Næs, 2012; Måge, Mevik, & Næs, 2008) or a parallel structure (Carroll, 1968; Dahl & Næs, 2006; Westerhuis, Kourti, & MacGregor, 1998). In the present paper we focus on multi-block models with a predictive direction, i.e. models in which a block can be either exogenous (input, predictor) or endogenous (output, dependent). Examples of such multi-block data structures, i.e. cases where both the predictor matrix X and the dependent matrix Y can be divided into several blocks, can be found within social science (Duncan & Hodge, 1963; Erlanger & Winsborough, 1976; Sang, Teo, Cooper, & Bohle, 2013), psychology (Cook, 1994;

Viswesvaren & Ones, 1995; Werts & Linn, 1970), sensory science (Bech, Juhl, Hansen, Martens, & Andersen, 2000; Martens, Tenenhaus, Vinzi, & Martens, 2007; Tenenhaus, Pagès, Ambroisine, & Guinot, 2005b), consumer science (Guinot, Latreille, & Tenenhaus, 2001; Menichelli, Hersleth, Almøy, & Naes, 2013; Næs, Brockhoff, & Tomic, 2010a; Olsen, Menichelli, Grunert, Sonne, Szabó, Bánáti, et al., 2011) and process control (Høskuldsson, 2008; Jørgensen, Segtnan, Thyholt, & Næs, 2004; Måge, Mevik, & Næs, 2008).

In particular, the so-called structural equation modelling (SEM) (or path modelling, PM) has obtained a strong position across many disciplines, in particular within the social sciences, because of its ability to analyze relations in complex networks of data blocks. Within the area of SEM, two main approaches exist for model estimation: the covariance-based approach and the component- based approach. Covariance-based SEM techniques, like LISREL (Jøreskog, 1978; Jøreskog & Sørbom, 1989), estimate path coefficients and loadings by minimizing the difference between observed and predicted covariance matrices (Hsu, Chen, & Hsieh, 2006). In this case the most widely used procedures to estimate parameters are the maximum likelihood (ML) and least squares (LS) methods. The component- based approach (Wold, 1982) provides instead estimates of the latent variables that are as closely related to each other as possible according to the actual path model and also to their corresponding manifest variables. The structural parameters are obtained as regression coefficients in the system of latent and manifest variables (Vinzi, Trinchera, & Amato, 2010). The PLS-PM technique is an important example of a component-based method. It appears that LISREL and PLS-PM are at present the two main methods for SEM modelling.

The SEM methods have a number of aspects and assumptions that seem to be traditionally accepted, but may in some applications not be suitable (Næs, Tomic, Mevik, & Martens, 2011). First of all, in the above mentioned approaches there is an underlying assumption of unidimensionality of the different blocks (Jøreskog & Sørbom, 1989; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005a; Vinzi, Trinchera, & Amato, 2010). This is linked to the tradition in social sciences of establishing series of questions representing one single underlying phenomenon (so-called scales, see e.g. Pliner & Hodben, 1992). This unidimensionality or rank-one assumption may, however, be questionable in many other types of applications. There is now on-going research within the PLS-PM tradition aiming at relaxing it (Vinzi, 2009; Vinzi & Russolillo, 2013). Within the LISREL tradition it is possible to handle also more than one dimension in each block, but the whole process of identification etc. becomes much more complex and it is as far as we know seldom done. Another assumption concerns the use of the same latent variable for being predicted and to be used for prediction. When a block is allowed to be multidimensional, this assumption is not at all obvious. For a deeper discussion of these aspects we refer to Næs et al. (2011).

A new method has recently been proposed (Næs, Tomic, Mevik, & Martens, 2011) that aims at analyzing path model structures, but from a different perspective than the standard SEM methods: the path modelling by Sequential and Orthogonalised PLS regression (SO-PLS). This is based on splitting the process into a sequence of modelling steps for each dependent block versus its predictive blocks. The estimation method is based on sequential use of orthogonalisation and PLS regression and benefits from a number of advantages (Jørgensen, Segtnan, Thyholt, & Næs, 2004; Næs, Tomic, Afseth, Segtnan, & Måge, 2013). For instance, the method is invariant to the relative scaling of the blocks, it allows for blocks with several components, it can easily handle collinearity and it can be used for determining the additional contribution of new blocks that are incorporated. The interpretation is based on the Principal Components of Prediction (PCP) method (Langsrud & Næs, 2003) but the different PLS regression models obtained can also be interpreted.

This paper explores the possibility of using SO-PLS in consumer acceptance studies, which has never been done before. Main emphasis will be on how the method can be applied and interpreted and also what type of advantages and possibly disadvantages this approach presents in this context, which is usually characterized by relatively weak relations between blocks (Næs, Lengard, Johansen, & Hersleth, 2010b). Focus will be on how the method handles multidimensionality of the blocks and how it can be used to combine individual variables, or specific blocks of variables, in more general blocks with a broader interpretation, such as for instance consumer habits, attitudes and demographic variables. It will be discussed how this can simplify analysis, at least for explorative purposes, as compared to other more traditional analyses. An application based on a consumer test on iced-coffees will be used as illustration.

2. Methodologies

2.1 The SO-PLS approach to path modeling

The SO-PLS approach to path modelling (Næs, Tomic, Mevik, & Martens, 2011) is based on the multi-block SO-PLS regression method. This is a regression method developed for estimating regression equations with N blocks of independent variables, i.e.

$$\mathbf{Y} = \mathbf{X_1 B_1} + \mathbf{X_2 B_2} + ... + \mathbf{X_N B_N} + \mathbf{E} \qquad (1)$$

where the **Y** represents the matrix of dependent variables, the **X**'s are the different blocks of input variables and the **B'**s are the regression coefficients. Throughout this paper we will assume that all variables are centred. The method is based on sequential use of orthogonalization and PLS regression (Fig. 1) which has number of favourable properties as mentioned above and which is described in detail in Næs et al. (2013). The procedure results in an estimated regression equation and various interpretation tools for the different blocks in relation to the response **Y**.

In the case of two input blocks, the SO-PLS method (Jørgensen, Segtnan, Thyholt, & Næs, 2004; Måge, Mevik, & Næs, 2008) first fits the output block **Y** to the first input block $\mathbf{X_1}$, thus identifying the column space of $\mathbf{X_1}$ that best fits the **Y** (space defined by the scores from the PLS regression). Then the same is done for the second input block, by fitting the estimated residuals to $\mathbf{X_2}$ after orthogonalisation with respect to $\mathbf{X_1}$ (i.e. with respect to the extracted PLS component scores of $\mathbf{X_1}$ for the first model). Since a part of $\mathbf{X_2}$ that can explain $\mathbf{Y}$ has already been involved in the first model, only the orthogonalised part is considered to contribute to better explained variance in $\mathbf{Y}$. We call this the additional contribution of $\mathbf{X_2}$. Orthogonalisation is used because of some important features: i) independence of the relative scaling of the blocks, ii) the possibility of having different dimensionality in each block and iii) a non-iterative estimation procedure (Næs, Tomic, Mevik, & Martens, 2011). In the case of N blocks, the algorithm alternates PLS regression and orthogonalisation N times.

When used in path modelling, the SO-PLS method is used independently for each endogenous block (Næs, Tomic, Mevik, & Martens, 2011). The endogenous block is used as the **Y** block, while all the blocks that have an arrow into the endogenous block (in the path diagram) are used as **X**-blocks. Each model is interpreted independently. It can be noted that none of the problems listed above (unidimensionality and requiring the same latent variable for prediction and to be predicted) exists with this approach. Note also that multicollinearity is handled easily since PLS regression is used (see Næs et al. (2011) for a more detailed description). In order to simplify interpretation in this context, the PCP method (Langsrud & Næs, 2003) is recommended for each model (each endogenous block), since it compresses all information in the model down to a loadings plot and a scores plot. First, the PCA is used for the predicted values, giving the PCA scores and the **Y**-loadings. Since the predicted values are already linear functions of the input blocks, these components are also linear functions of the input variables. The input **X**-loadings are thus obtained as the regression coefficients of these linear combinations.

For the practical implementation of this method, what one needs to do first is to establish the dependence diagram from the actual path model (Fig. 2). The diagram (Fig. 2.b) contains more or less the same information as in the original path model (Fig. 2.a), but presents all relations in such a way that one can read directly the order of the incorporation and thus orthogonalisation. One always starts from left and, as can be seen, in this case $\mathbf{X_1}$ is incorporated first. Thereafter $\mathbf{X_2}$ is orthogonalised with respect to $\mathbf{X_1}$. In this case, the process is quite obvious but, for more complex path diagrams, one needs a procedure for how to establish the dependence order. The criterion for the order, as proposed in Næs et al. (2011), is that a block with only a direct relation to the output (e.g. $\mathbf{X_2}$ in Fig. 2) is orthogonalised to another one with a more complex relation, since it is often the most natural block to consider the additional effect of in the path model. In other words, the blocks with the most complex contributions (measured by the number of relations) are considered first, ending up with the block(s) with only a direct relation. In case of two blocks having the same relation to the output, one can choose the order based on what one is most interested in considering first. For more details we refer to the example below and to Næs et al. (2011).

It should also be stressed that a separate model is estimated for each endogenous block. This means that every endogenous block in the path is modelled as response for the blocks that are exogenous to it. For the example in Fig. 2, the following models are considered:

- $\mathbf{X_2}$ predicted from $\mathbf{X_1}$;

- $\mathbf{Y}$ predicted from $\mathbf{X_1}$ and $\mathbf{X_2}$, with $\mathbf{X_2}$ orthogonalised to $\mathbf{X_1}$.

For each regression model, once the predicted values are estimated, the PCP method uses these values as input to a PCA (usually after back-fitting to original units of X_2, see Næs et al. (2011) for details) so that the number of components is reduced and focus is given on the main variation in the dependent block that can be explained.

For determining the number of components for the different input blocks, an evaluation of the cross-validated prediction results is needed. For this purpose, the same plot as proposed by Måge and colleagues (Måge, Mevik, & Næs, 2008) is used for selecting the best possible combination of factors (i.e. with the lowest prediction error) for the input blocks. Two possible alternatives can be considered: the first one aims at finding the factor combinations with the best overall prediction ability (full optimisation of all components simultaneously), the other one optimises the number of components in the first block first, then in the second one keeping the first fixed and so on (sequential optimisation).

Note that this method does not require any careful investigation of unidimensionality and that it does not require a distinction between a measurement model and a structural model, which is needed instead for standard SEM methodology. Both aspects are implicitly involved by the use of the PLS for each block and in the relations between the blocks given by the path diagram. As such the method is regression oriented, pragmatic and thus particularly useful for explorative analysis.

3. Case study

3.1 Data set

In this study 100 users of iced-coffee were recruited (Norway, winter 2012) for participating in a central location test on iced coffee. A total of 12 different iced-coffees were presented in randomized monadic order in the form of a mock-up product (a picture on the computer screen, no tasting was involved). The iced-coffees vary according to a fractional factorial design based on 4 extrinsic conjoint attributes (Table 1): calorie content (60 kcal or 90 kcal per 100 ml), origin (Norway or Italy), price (17, 23 or 29 norwegian krones) and type of coffee ("latte" or "espresso", corresponding to mild or strong). Consumers were asked to imagine that they were going to buy iced-coffee and indicate how likely it is that they would choose these products. The probability of buying was evaluated on a 9-point scale, with 1 = ''not very likely'' and 9 = ''very likely'. After the evaluation of the first 6 products, a break was introduced and consumers were informed that other 6 pictures of iced-coffees were left.

Finally, a number of consumer characteristics related to demographics, habits and attitudes were recorded. For the purpose of this paper, only the relevant aspects for illustrating the proposed methodology will be covered.

Main focus here will be on how the consumer characteristics are related to the individual probability of buying pattern. As was discussed in Menichelli et al. (2013), there exist a number of ways that the blocks can be organised for this purpose. In the mentioned paper it has been shown that the best solution is to use the consumers as rows in the data matrix and use the probability of buying for the different products as separate columns. The different variables in the consumer characteristics data set are also used as separate columns. The advantage of this approach is that it can be used to highlight the interactions between consumer characteristics and the different product characteristics. The method must, however, also be accompanied with a separate ANOVA study of the main effects and interactions of the product attributes. The analysis is therefore a two-step procedure, first an ANOVA and then a path modelling method based on the second approach in Menichelli et al. (2013).

3.2 Organisation of the data blocks and paths

Consumer characteristics data can sometimes be split into blocks of data according to their nature and with a structure among them. How to decompose the data depends on the specific situation, the problem to be addressed and the collected information available (Menichelli, Hersleth, Almøy, & Naes, 2013). In this paper we will consider the following consumer characteristics blocks (see also Table 2). Note that, instead of splitting into smaller blocks after a prior careful analysis of unidimensionality, we will here approach the system with broader categories, which is one of the primary advantages of the SO-PLS method.

- **Demographics**. Gender and age information is available for each consumer, thus a demographic data block is created. The age variable is organized as a dichotomous (i.e. binary) variable with two levels corresponding to two evenly spread age groups (20-36 and 37-60). The first age range is coded by 1 and the second by 0. For the gender variable, the value 1 is used for females and 0 for males. The demographics block is thus represented by two dummy variables.
- **Importance of attributes**. The importance of the extrinsic attributes (i.e. the factors used in the factorial design) was evaluated on a scale from 1 to 5, with 1 meaning "not important at all" and 5 "very important". Thus a block including four manifest variables (importance of: coffee type, calorie content, origin, price) is created.
- **Consumption habits.** Two consumption habit questions were also included in the questionnaire. One is related to the usage frequency in the last two months, evaluated on a scale from 1 ("less than once per month") to 5 ("three or more times per week"). The other question asks to indicate for how long the consumer has drank iced-coffee on a scale from 1 to 3, with 1= "less than one year and a half", and 3= "three years or more". These two variables are collected in an additional block.
- **Neophobia.** In the questionnaire there were also present three "food-neophobia" statements. Consumers had to evaluate their agreement with each of the statements on a 1-to-7 point scale, with 1 meaning "completely disagree" and 7 "completely agree". A new attitude block of three manifest variables is thus considered.

The acceptance data, as was discussed above and as recommended in the study of Menichelli et al. (2013), is represented by probability of buying scores of each consumer (rows) for each of the 12 iced- coffees (columns). The output block thus contains twelve variables. The probability of buying is consumer centered for avoiding the effect of a different use of the scale. Note that, since the SO-PLS method uses centred variables, the probability of buying matrix will be double centred. In order to balance the variation of the variables within each block, the variables are also standardised. Note, however, that the relative scale of the different blocks does not influence the results when SO-PLS is used.

In this paper we will assume that all the blocks of consumer characteristics can influence the probability of buying. In addition we will assume that the demographic variables can influence the importance of attributes, the neophobia and the consumption habits. Finally we will assume that both the importance of attributes and the neophobia may have an influence on consumption habits. All these relations are natural and useful to consider. No attempt will be made to interpret the results in a causal context. Note also that the importance of attributes block and the neophobia block are parallel in the sense that they influence and are influenced by the same blocks. The block to consider first in the dependence diagram is thus a matter of taste. These relations are depicted in Fig. 3 and will be the basis for the path modelling analyses.

The dependence diagram (Fig. 4) is structured in relation to the path model and to the considerations given about the orthogonalisation step in section 2.1. Accordingly, the demographic block is coming as first since this is involved in all relations. Then the importance of extrinsic attributes and the neophobia blocks should be considered after the demographics; both alternative combinations (both orders) have been tried and the results are the same. Thus we chose to have neophobia as second and the importance of extrinsic attributes as third block. The consumption habits block is included as last in the model for explaining the probability of buying, since it has only a direct relation to it. Note that the dependence diagram presents the order of the blocks for each of the models. From the dependence diagram (Fig. 4) one can see that there are four endogenous blocks, meaning that four independent models will be estimated:

- Model 1: neophobia predicted from demographics;
- Model 2: importance of extrinsic attributes predicted from demographics and neophobia, with neophobia orthogonalised with respect to demographics;
- Model 3: consumption habits predicted from demographics, neophobia and importance of the extrinsic attributes, with neophobia orthogonalised to demographics and importance of attributes orthogonalised to both demographics and neophobia;
- Model 4: probability of buying predicted from all the other blocks, also here with orthogonalisation according to the order indicated in the dependence diagram (Fig. 4).

Each model is fitted by the SO-PLS method and then interpreted through the use of PCP. This gives four models to consider but, as will see, the first vanishes due to lack of predictive power.

4. Results

4.1 ANOVA model

A mixed model ANOVA has been performed for explaining the consumer probability as a function of the consumer and the four extrinsic conjoint factors (see section 3.1). This step is necessary when organizing the data sets according to the approach 2 proposed in Menichelli et al. (2013), since this approach does not focus on product effects but on interactions between products information and consumer characteristics. The model considers as fixed the main effects of the conjoint factors and four (out of the six possible) two-way interactions (see below), while the consumer effect and its interactions with the conjoint factors are random. Note that, because of the fractional factorial design adopted for the experiment, some of the interactions are confounded. The model is the following:

Probability of buying = mean + Coffee type + Calorie content + Country of production + Price + Consumer
*+ Price * Calorie content + Coffee type * Calorie content + Calorie content * Country of production + Price * Coffee type*
*+ Consumer * Coffee type + Consumer * Calorie content + Consumer * Country of production + Consumer * Price + random noise*

Adding more interactions is impossible due to confounding. Results (not shown) indicate that calorie content and price are significant at 5% significance level. Moreover consumers would on average have a tendency of buying iced coffees with low calorie content and low price. Only one interaction between conjoint factors is close to be significant at 5% level: *Calorie content * Price.* Taking this into account does not change the conclusions. We refer to Asioli and colleagues (Asioli, Næs, Granli, & Almli, 2013) for a detailed description of the conjoint study and results.

4.2 The dimensionality of the blocks

As already mentioned, the SO-PLS approach to PM allows for different dimensionality for the blocks. From the values of explained variances in Table 3, it is quite clear that at least for some of the blocks there is more than one dimension. The probability of buying block is at least three-dimensional. As indicated above, multidimensionality of the blocks can also open up for the possibility that the predictable part of an endogenous block is different from the part of the same block that is useful for prediction. This concept has never been considered before in the path modelling context and will be discussed in the following.

4.3 SO-PLS approach to PM

In order to find the best possible number of components we use the Måge plot based on cross-validation (Måge, Mevik, & Næs, 2008). The total number of components for the blocks is on the horizontal axis, while the RMSEP is on the vertical axis. As can be seen from the RMSEP plot for model 4 (Fig. 5.a.), the results with the best prediction ability are given by using 1 component in the demographics and neophobia blocks, 3 components in the block of the importance of the extrinsic attributes, no components in the consumption habits block. Eliminating the demographics block gives, however, almost the same results in terms of prediction ability. As can also be seen from the plot, the sequence of improvement along the lower line is exactly the same as the one obtained by the sequential choice of components. In other words, sequential and optimal choice of components gives essentially the same results in this case. Table 4 indicates both calibrated and validated variances, which follow each other in a natural way. Note that the predictions abilities are quite low, which corresponds well with results found in other studies of this type (Menichelli, Hersleth, Almøy, & Naes, 2013; Næs, Lengard, Johansen, & Hersleth, 2010b).

The difference between the two ways of finding the number of components is clearly shown for model 2 (Table 4): the demographics block vanishes from the former (Table 4.a.) while has one component as optimal number for the latter (Table 4.b.). This means that the demographic information can be used for prediction, but a similar predictive power can also be contained in the neophobia block if global optimisation is used. Note, however, that differences are small and should not be over interpreted. In model 3 the consumption habits are well explained by the demographics. For model 4 it is primarily the importance of the extrinsic attributes which contains the relevant information. For model 1 there is not predictive power and this model will therefore not be considered further. In the following we will put main emphasis on model 4 and only discuss more briefly the results from the other two models. Note that from the same tables we get information about the additional importance of incorporating a block. For instance for model 4 it is clear that the additional contribution of the importance of attributes block is stronger than the importance of the neophobia block.

In the Y-loadings plot for model 4 (Fig. 5.b.), the first axis discriminates between the two coffee types, i.e. espresso iced-coffees on the positive side and latte iced-coffees on the negative side. The second component splits the products according to country of production and price: from positive to negative values of this component one first finds the expensive Norwegian iced-coffees, then the medium-low price Norwegian products together with the expensive Italian products, finally the medium-low price Italian iced-coffees. The first two PCP components explain together 81% of the variance of the predicted Y. The interpretation of third component (9.9% of the predicted explained Y-variance) is also related to both country of production and price, while the fourth component (8.1% of the predicted explained Y-variance) is clearly discriminating between the high (on the positive values) and low calorie content products.

The X-loadings plot for model 4 (Fig. 5.c.) shows indeed that both the neophobia variables and the importance of attributes variables are the ones spreading the PCA space the most, as also indicated in Table 4. The position of the demographic variables (note that according to above they have a very low predictive power) indicates that the female and young consumers give more importance to calorie content and price than to country of origin and coffee type.

Moreover, the consumers lying on the left-hand side of the scores plot (not shown) that stick to the usual food are opposite to the ones that like to choose new flavors and try new food. These food-neophobic consumers will thus more likely buy the products on the left-hand side of the Y-loadings plot, i.e. the latte iced-coffees. The second component in the X-loadings plot suggests that consumers willing to experience new food and giving high importance to price will probably buy medium-low price Italian products. The neophobia variables dominate also the third component (not shown) together with the importance of country of production, indicating how consumers that stick to usual food prefer Norwegian products, in contrast with those consumer that are willing to try new flavors and food and thus to buy the Italian iced-coffees. Food neophobic consumers that also give high importance to price would probably buy the medium price- cheap Norwegian iced-coffees, while they do not have any clear preference in price when the products are Italian. Finally, the fourth component is clearly dominated by the importance of calorie content, which is positively related to those products having 60 kcal (instead of 90 kcal) per 100ml.

As can be seen from the Table 4, model 1 has no predictive power and will not be considered further. The results from model 2 (Fig.6) indicate that most of the variability in the importance of attributes block is linked to the differentiation between not neophobic and neophobic attitudes (the first component explains 79% of the predicted Y-variance, see Table 5). Those consumers that want to stick to the usual food give main importance to the country of production, being opposite to those consumers willing to try new food and to choose new flavors. The second component (21% of the predicted Y-variance) indicates that those consumers that care about the coffee strength have the attitude of trying new food, while a high importance of price is more related to the willingness of choosing new flavors. Model 3 (not shown) suggests the use of one component for the demographic block and zero components for neophobia and importance of attribute blocks in order to predict the consumption habits. Results for this model highlight that female consumers started to drink iced-coffee a relatively long time (more than three years) ago and sooner than male consumers.

Considering the amount of information accounted for in the predicted Y-values (Table 5), it is clear that at least the importance of the extrinsic attributes block (model 2) and the probability of buying iced-coffee (model 4) are two-dimensional. In model 4, the first two components describe respectively about 59% and 22% of the information.

It should finally be highlighted that the SO-PLS method in this case also indicates that the same information in a block is not necessarily used for prediction and to be predicted. From Table 5 one can see that the dimensionality is 2 for the predicted Y (the importance of attributes block), while Table 4.a. shows that 3 dimensions of the same block are needed to predict the probability of buying.

5. Discussion and conclusions

The assumption of unidimensionality

For standard SEM approaches it is assumed that each block is unidimensional. This is natural in many cases in the social science where each block often represents a battery of related questions used to define one single aspect (Tenenhaus, Pagès, Ambroisine, & Guinot, 2005b; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005a; Vinzi, Trinchera, & Amato, 2010). For this reason the probability of buying data, using the second model structure in Menichelli et al. (2013), needs to be split up in such a way that each product represents its own block. One possible way of simplifying this is obtained by using PCA on the probability of buying values (Menichelli, Hersleth, Almøy, & Naes, 2013) and by organising the information into a few blocks corresponding to the few most important principal components.

The unidimensionality assumption has to be satisfied also for the input data. As already mentioned, the consumer characteristics blocks are here found to be multidimensional (Table 3), thus a proper splitting into more than one block has to be achieved for each of them.

For the SO-PLS methods, however, these considerations are not necessary since the standard PLS (PLS-2 in this case) can be used directly without any prior consideration of dimensionality. This implies that one can also construct more general blocks (like for instance consumer habits) containing several related variables, and in this way obtain information not only about how the variables in the block are related, but also about how they as a block influence other blocks. This may simplify analysis considerably.

Same dimension used for prediction and to be predicted

When one opens up the possibility of using several dimensions in each block, the same dimensions are not necessarily used for prediction and to be predicted. This was demonstrated for one of the blocks above (see section 4.3).

Interpreting several models

The SEM approaches has the advantage that they give one model containing all the blocks. For the SO-PLS approach one has to consider one model for each endogenous block. This may at first sight seem a bit complex but, as was seen here, each model can be simplified by the use of PCP. In this case only three scores plots and loadings plots revealed all the essential information. In other words, in up to moderately complex cases, this should not represent any serious problem. If there are too many blocks, one could also consider merging some of them.

Explorative versus confirmative analysis

From the above it has been shown that the SO-PLS can be used to reveal important relations in the context of consumer science and particularly in the presence of very different types of information such as product attributes, consumer characteristics and consumer acceptance. The method provides a number of advantages that are related to simplicity and not relying on unrealistic assumptions. The SO-PLS is, however, more explorative in nature than standard SEM models. We therefore suggest that the investigator considers the option of using a more confirmative analysis afterwards based on the results obtained. Further development of SO-PLS is in progress for obtaining better possibilities for significance testing.

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Product	Coffee type (strength)	Calorie content (kcal per 100 ml)	Country of production	Price (Norwegian crones)
1	Espresso	90	Italy	29
2	Latte	90	Norway	23
3	Latte	60	Norway	23
4	Espresso	60	Norway	17
5	Latte	90	Norway	29
6	Espresso	60	Norway	29
7	Espresso	90	Norway	17
8	Latte	90	Italy	17
9	Latte	60	Italy	29
10	Espresso	90	Italy	23
11	Latte	60	Italy	17
12	Espresso	60	Italy	23

Table 1. The factorial design used in the iced- coffee study. Twelve products varying according to coffee type, calorie content, country of production and price are considered.

X_1	Demographics
x_{11}	Age
x_{21}	Gender
X_2	**Neophobia**
x_{12}	I'm usually among the first ones to try out new food
x_{22}	It's nice to have the possibility to choose among new flavors
x_{32}	I prefer to stick to the foods I'm used to (reversed)
X_3	**Importance of attributes**
x_{13}	When you choose iced-coffee, how important is the coffee strength for you?
x_{23}	When you choose iced-coffee, how important is the calorie content for you?
x_{33}	When you choose iced-coffee, how important is the country of production for you?
x_{43}	When you choose iced-coffee, how important is price for you?
X_4	**Consumption habits**
x_{14}	In the last two monts, how often have you drank iced-coffee?
x_{24}	How long have you drank iced-coffee?

Table 2. The input blocks of consumer characteristics.

	Demographics	Neophobia	Importance of attributes	Consumption habits	Probability of buying
Pc-1	65	63	36.5	71	47
Pc-2	35	21	28.5	29	23
Pc-3		16	20		10
Pc-4			15		7

Table 3. The explained variances (%) of the first four PCA components for the different consumer characteristics and the probability of buying show the multidimensional nature of the blocks.

a.

	Model 1		Model 2		Model 3		Model 4	
Demographics	0	0	0	0	6.5	3.8	2.3	0
	[0]		[0]		[1]		[1]	
Neophobia			6.3	1.9	6.5	3.8	8.5	3
			[2]		[0]		[1]	
Attributes importance					6.5	3.8	18.7	7.5
					[0]		[3]	
Consumption habits							18.7	7.5
							[0]	

b.

	Model 1		Model 2		Model 3		Model 4	
Demographics	0	0	2.6	0.3	6.5	3.8	0	0
	[0]		[1]		[1]		[0]	
Neophobia			6.1	1.0	6.5	3.8	5.5	2.5
			[1]		[0]		[1]	
Attributes importance					6.5	3.8	16.6	7.5
					[0]		[3]	
Consumption habits							16.6	7.5
							[0]	

Table 4. Explained Y-variances (calibrated on dark surface, on the left hand side of each cell, validated on light surface) for the different input matrices in all the four models. Both global (a.) and sequential (b.) optimisation of the number of components has been calculated. Incremental values can be obtained as differences between the percentages given. The values in square brackets are the number of components needed.

	Model 1	Model 2	Model 3	Model 4
Component 1	0	79.2	100	59.2
Component 2		20.8		21.8
Component 3				9.9
Component 4				8.1

Table 5. Explained variances (in %) of the predicted Y for the four models after 1, 2, 3 and 4 components.

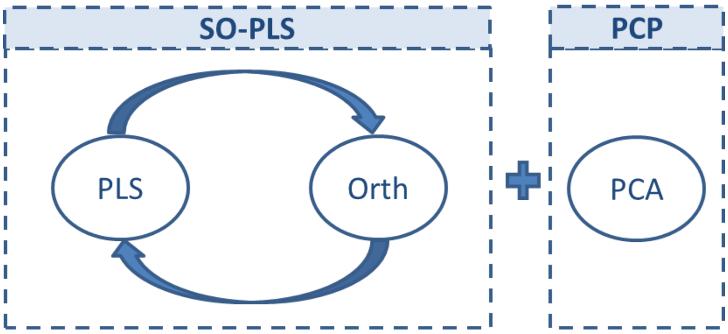
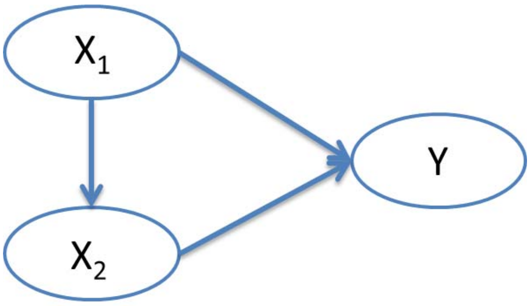


Fig. 1. Path modelling by the SO-PLS procedure. In the SO-PLS step, the output block is fitted to the first input block by PLS, then the same is done for the other(s) input block(s) after orthogonalisation (i.e. with respect to the extracted PLS component scores of the previous block). The PCP step is then graphically higlighting the main variation in the output block that can be explained: the predicted values are used as input in a PCA. This means that the predicted principal component scores are linear functions of linear functions of the input data.

a.



b.

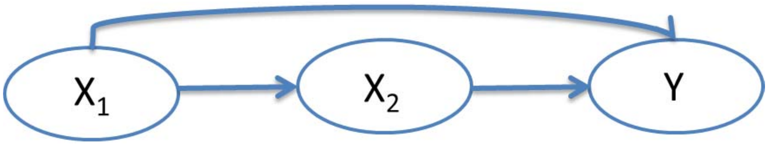


Fig. 2. Example of a path diagram (a.) and the related dependence diagram (b.) with two input blocks.

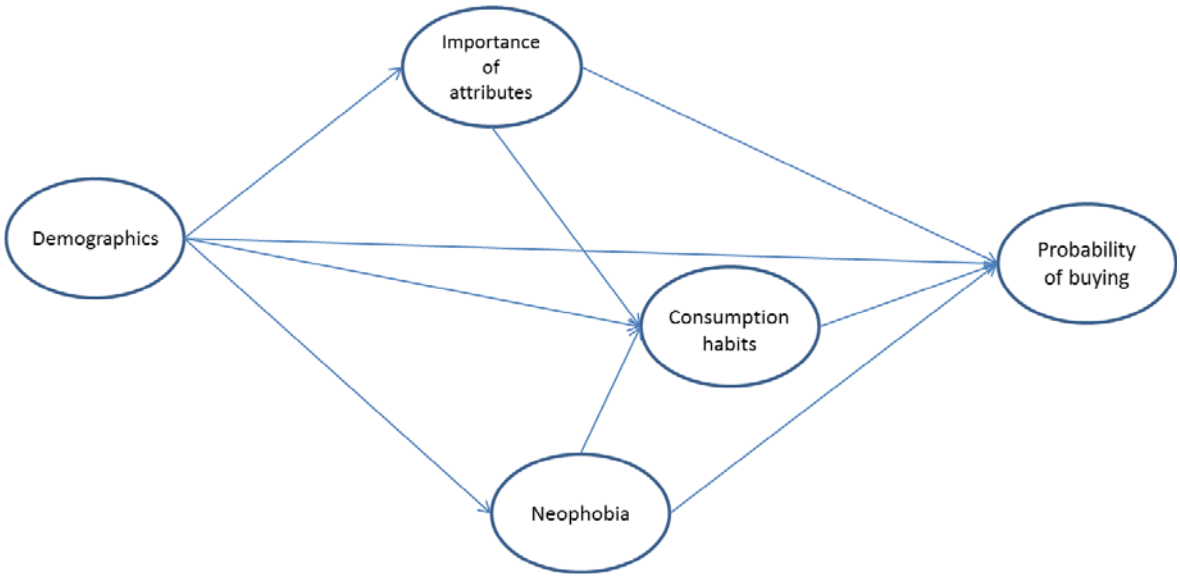


Fig. 3. The path model indicates how the blocks of consumer characteristics are assumed to be related to each other and to the consumer probability of buying for the 12 iced-coffees.

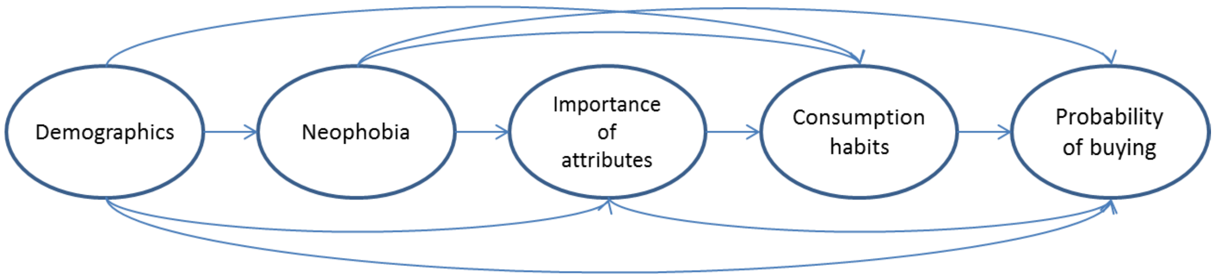
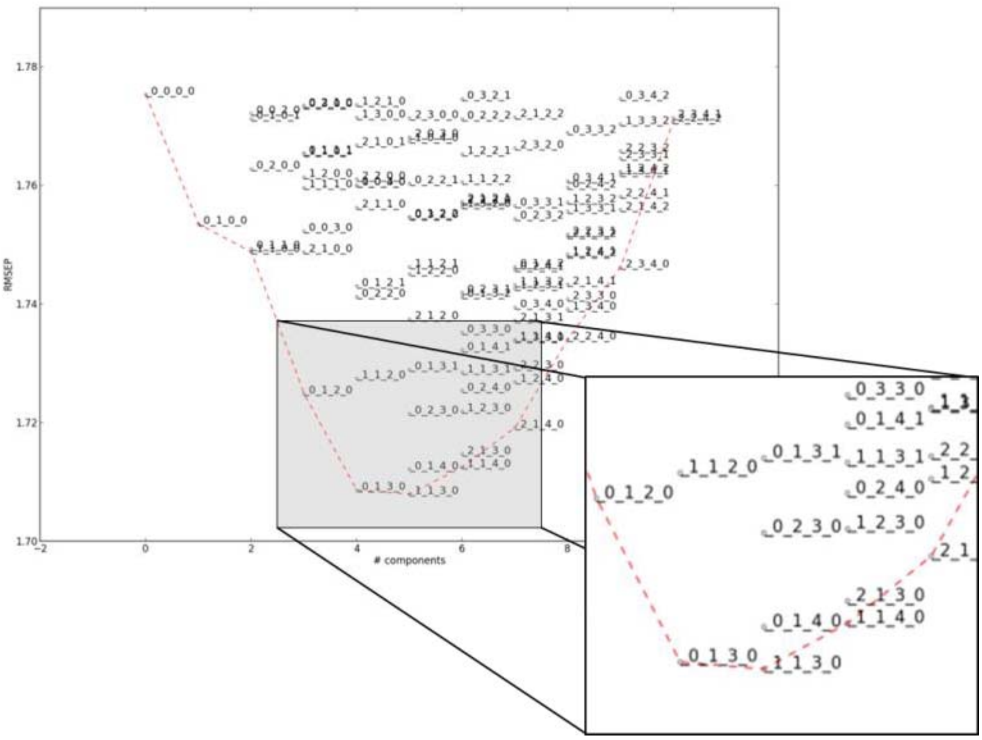


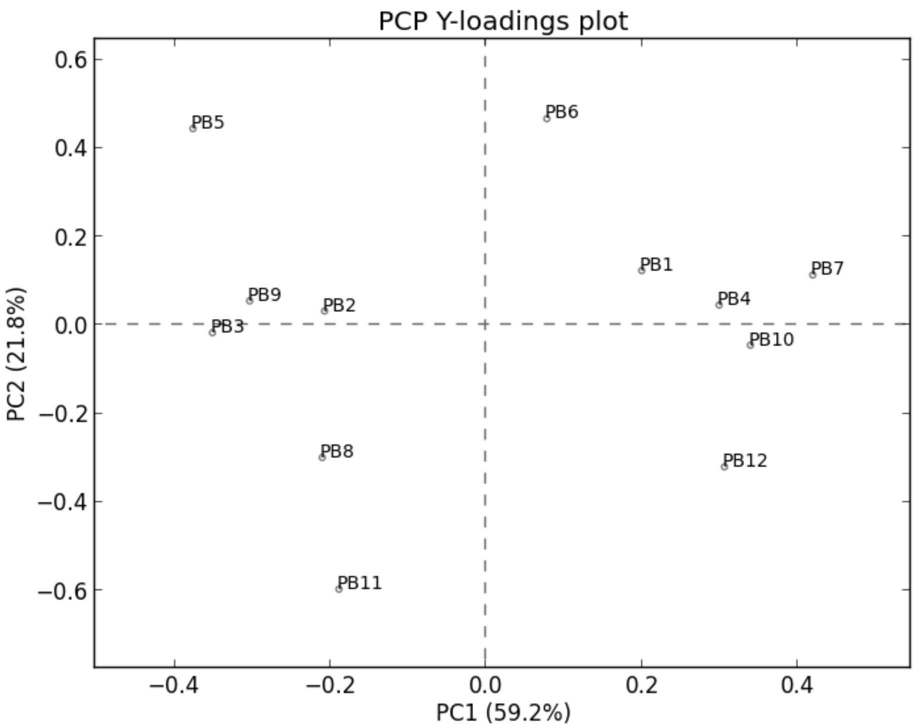
Fig. 4. The dependence diagram shows the order of the consumer characteristics blocks that is considered in the SO-PLS approach to PM for explaining the probability of buying.

a.



RMSEP
components
1.78
1.76
1.74
1.72
1.70
-2
0
2
4
6
8
0_0_0_0
0_1_0_0
0_1_2_0
0_1_3_0
1_1_3_0
0_3_3_0
0_1_4_1
1_1_2_0
0_1_3_1
1_1_3_1
0_2_4_0
0_2_3_0
1_2_3_0
2_1_3_0
0_1_4_0
1_1_4_0

b.



PCP Y-loadings plot
PC2 (21.8%)
PC1 (59.2%)
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.4
−0.2
0.0
0.2
0.4
PB5
PB6
PB1
PB7
PB9
PB2
PB4
PB3
PB10
PB8
PB12
PB11

c.

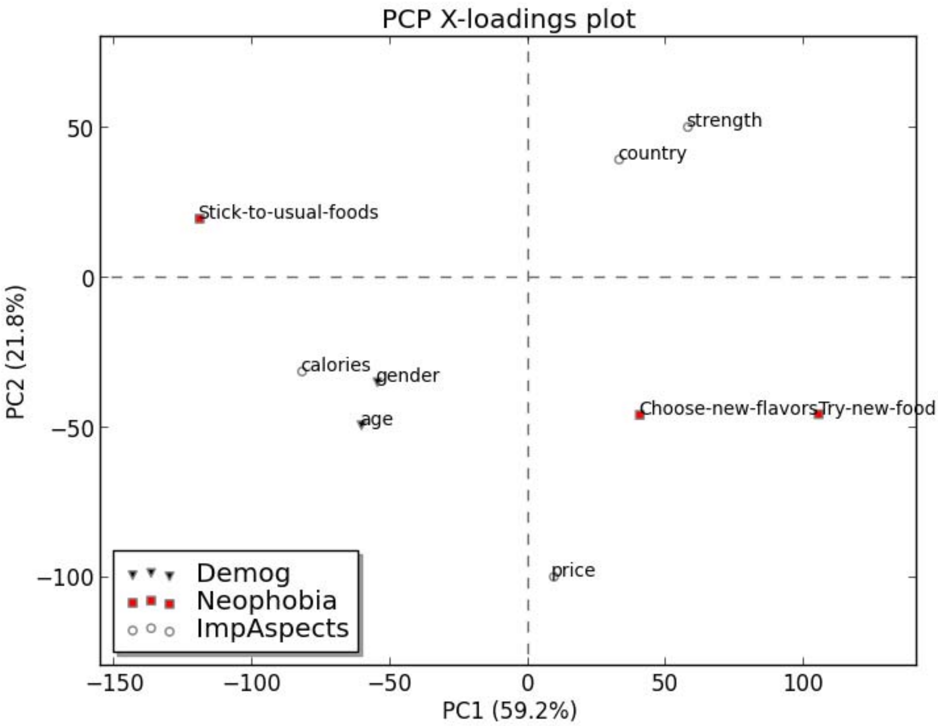
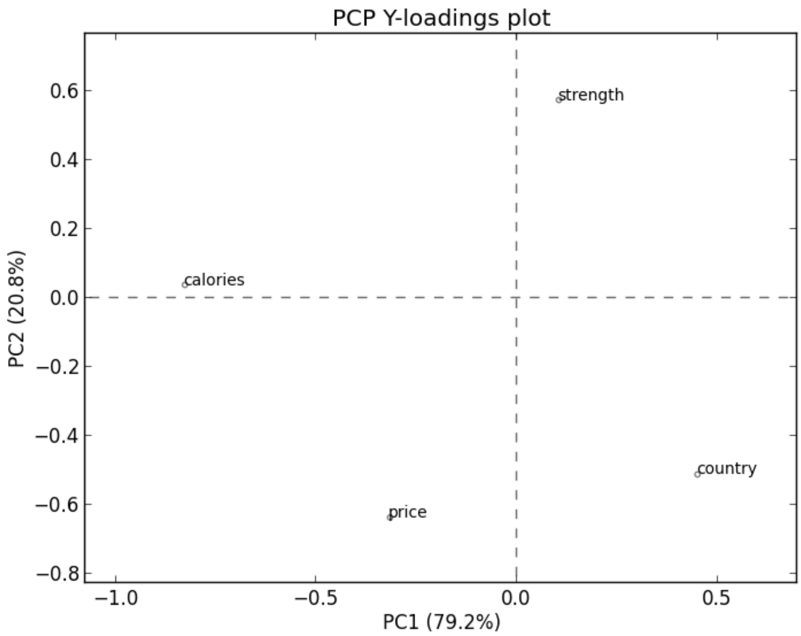


Fig. 5. Results from the SO-PLS approach to PM for model 4: (a.) RMSEP plot for deciding the optimal number of components in the blocks, (b.) Y-loadings plot and (c.) X- loadings plot.

a.



b.

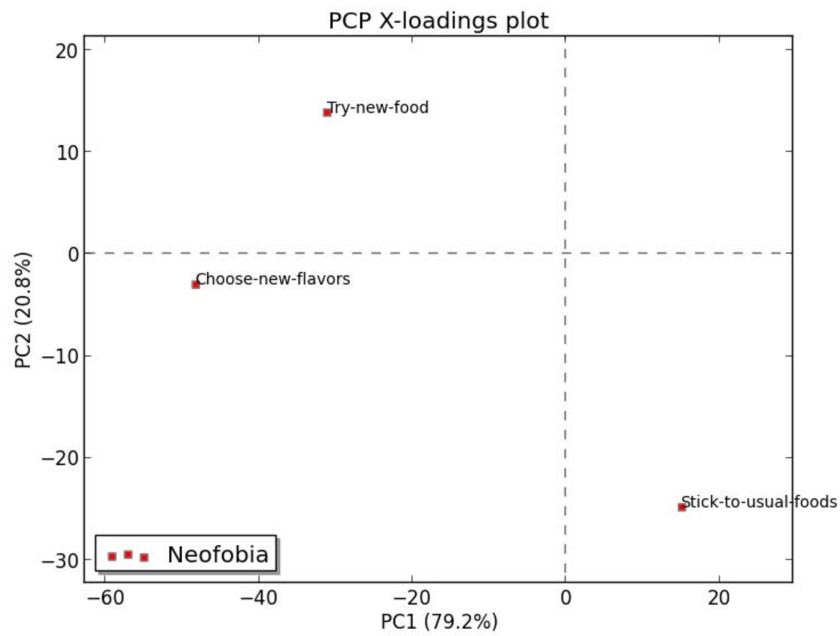


Fig. 6. Y-loadings plot (a.) and X- loadings plot (b.) for model 2.