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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.