Food Quality and Preference 32 (2014) 65–76

Contents lists available at SciVerse ScienceDirect

Food Quality and Preference

journal homepage: www.elsevier.com/locate/foodqual

Penalty analysis based on CATA questions to identify drivers of liking and directions for product reformulation

Gastón Ares [a,*], Cecilia Dauber [a], Elisa Fernández [a], Ana Giménez [a], Paula Varela [b]

[a] Departamento de Ciencia y Tecnología de Alimentos, Facultad de Química, Universidad de la República, General Flores 2124, CP 11800, Montevideo, Uruguay
[b] Instituto de Agroquímica y Tecnología de Alimentos, Avda. Agustín Escardino 7, 46980 Paterna, Valencia, Spain

ARTICLE INFO

Article history:
Received 28 August 2012
Received in revised form 27 March 2013
Accepted 27 May 2013
Available online 4 June 2013

Keywords:
CATA
Apples
Yogurt
Consumer studies
Product optimization

ABSTRACT

One of the most important steps of new product development process is product optimization, which aims at identifying consumers' ideal products and directions for product reformulation. The present work proposes the application of a penalty analysis based on consumer responses to CATA questions to identify drivers of liking and directions for product reformulation. Two studies were conducted in which 74 and 119 consumers evaluated a set of samples (5 apples and 8 yogurts) using a check-all-that-apply question related to sensory characteristics and were also asked to check all the terms they considered appropriate to describe their ideal product. Data were analyzed by counting the number of consumers who did not check an attribute as they did for their ideal product, and its associated mean drop. A dummy variable transformation approach was proposed to make linear regression models between CATA terms and overall liking scores using Partial Least Squares (PLS). Juiciness, sweetness, apple flavor, firmness and crispiness were the most relevant attributes for consumers in the apple study. Meanwhile, in the yogurt study smoothness, homogeneity and creaminess were the main drivers of liking and were responsible for the highest penalization on overall liking (more than 1 in the 9-point hedonic scale). PLS regression enabled the identification of the attributes which deviation from the ideal caused a significant decrease in overall liking. Penalty analysis on CATA questions proved to be a simple and useful approach to identify drivers of liking and directions for improving the products in both studies. Advantages and disadvantages of this approach are discussed, as well as directions for further research.

1. Introduction

New product development has been regarded as a strategy for gaining competitive advantage and long-term financial success (Costa & Jongen, 2006). The implementation of a market-orientation and consumer-driven approach has been recognized as the best way to develop successful products (Grunert, Baadsgaard, Larsen, & Madsen, 1996; Stewart-Knox & Mitchell, 2003). The main stages of a consumer-driven new product development process are: identification of consumer needs, development of an idea to address those needs, product design to substantiate the idea and the product's market introduction (Urban & Hauser, 1993). Within product design, one key step is the selection of a product formulation that is aligned as much as possible with consumer sensory preferences (van Kleef, van Trijp, & Luning, 2006). In this context, one of the main challenges for Sensory and Consumer Science is to provide actionable information for making specific changes in product formulation, and not just product descriptions (Moskowitz & Hartmann, 2008).

Over the years, many strategies have been used in new product development to identify the sensory attributes that drive consumer preferences and the characteristics of the ideal product, i.e. the product that maximize consumer liking (Lagrange & Norback, 1987). A popular approach has been the application of preference mapping, which consists of a group of techniques that are able to relate consumer liking scores of a large set of products with their sensory characteristics as evaluated by a trained assessor panel (van Kleef et al., 2006). Considering the time and resources associated with creating and training trained assessor panels, particularly for specific applications during new product development, consumer-based sensory characterization has gained popularity in the last decade (Varela & Ares, 2012). Moreover, trained assessors may describe the product differently to consumers and/or evaluate attributes that may be irrelevant for consumers, consumer-driven sensory characterization of products could have greater external validity (ten Kleij & Musters, 2003). Thus, product optimization is increasingly being performed by asking consumers to describe the sensory characteristics of food products.

Just-about-right (JAR) scales have been one of the first and simplest consumer-based approaches to get information about the optimum intensity of sensory attributes (Popper & Kroll, 2005).

* Corresponding author. Tel.: +598 29248003.
E-mail address: gares@fq.edu.uy (G. Ares).

0950-3293/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.foodqual.2013.05.014

In this approach consumers are asked to evaluate a set of attributes as deviations from their ideal, by indicating if its intensity is too strong, too weak or just-about-right (Lawless & Heymann, 2010). Penalty analysis on data from JAR has been used to identify the sensory attributes that have the largest influence on consumer liking and to identify directions for product reformulation (Plaehn & Horne, 2008). As an alternative, Xiong and Meullenet (2006) introduced a partial least squares (PLS) regression approach to study the relative influence of attributes on consumer liking. Penalty analysis on data from JAR scales enables the identification of the products which are closer to the ideal, the direction in which an attribute should be changed if it is not in its optimum or JAR level and how much liking is affected when an attribute is not JAR (Lesniauskas & Carr, 2004). Despite their popularity and the fact that they provide actionable information, the application of JAR scales in product optimization has raised several concerns. This type of task could make consumers focus on sensory characteristics that they would not normally do (Popper & Kroll, 2005), leading to changes in their hedonic perception (Ares, Barreiro, & Giménez, 2009; Epler, Chambers, & Kemp, 1998; Popper, Rosentock, Schraidt, & Kroll, 2004).

Intensity questions have been reported to have a smaller influence on consumer liking and have been recommended for product optimization by some authors (Moskowitz, 2001; Popper et al., 2004). Considering that consumers are able to rate attribute intensity (Husson, Le Dien, & Pagès, 2001; Moskowitz, 1996; Worch, Lê, & Punter, 2009) and assuming that they have an implicit ideal in their minds (Moskowitz, 2003), Van Trijp, Punter, Mickartz, and Kruithof (2007) proposed the Ideal Profile method for identifying ideal products. In this approach consumers are asked to directly rate attribute intensity for their ideal product using unstructured scales. Although this method has been shown to provide accurate descriptions of ideal products that are similar to the most liked products (Worch, Dooley, Meullenet, & Punter, 2010; Worch, Lê, Punter, & Pagès, 2012a, 2012b) and actionable information for product reformulation similar to that provided by JAR scales, it could be difficult and not intuitive for consumers to rate the ideal intensity of a large set of attributes using scales.

Check-all-that-apply (CATA) questions have been gaining popularity for sensory characterization of food products by consumers due to their simplicity and ease of use (Adams, Williams, Lancaster, & Foley, 2007; Ares, Barreiro, Deliza, Giménez, & Gámbaro, 2010; Ares, Varela, Rado, & Giménez, 2011a; Dooley, Lee, & Meullenet, 2010; Plaehn, 2012). In this approach, consumers are presented with a list of terms and are asked to select all the terms that they consider appropriate for the product. The relevance of each term is determined by calculating its frequency of use. CATA questions have been reported to be a quick, simple and easy method to gather information about consumer perception of the sensory characteristics of food products; having a smaller influence on liking scores than just-about-right or intensity questions (Adams et al., 2007).

Plaehn (2012) proposed a penalty analysis on data from CATA questions to identify the relative importance of emotional attributes on overall liking scores of a set of citrus flavored sodas. Considering that CATA questions have been used to identify the sensory characteristics of consumer ideal product (Ares, Varela, Rado, & Giménez, 2011b; Cowden, Moore, & Vanluer, 2009), a penalty analysis approach could be used to identify how much overall liking is reduced because of the deviations in sensory profiles between real and ideal products, as detected by a CATA question.

In this context, the aim of the present work was to identify drivers of liking and directions for product reformulation by applying a penalty analysis based on consumer responses to CATA questions about a set of samples and their ideal product.

2. Materials and methods

Two studies were carried out in which consumers were asked to answer a CATA question to describe a set of samples and their ideal product. In the first study consumers were asked to score their texture liking and to describe the texture of eight yogurts formulated following a factorial design. In the second study consumers evaluated their overall liking of five commercial apple cultivars and completed a CATA question which included odor, flavor and texture characteristics. Penalty analysis based on consumer responses to the products compared to their ideal product was used to identify drivers of liking and directions for product reformulation.

2.1. Study 1: yogurt study

2.1.1. Samples

Eight yogurts were formulated by modifying the fat content of the milk, and the concentration of gelatin and modified starch (National 465, National Starch, Trombudo Central, Brasil), following a 2^3 full factorial design. These variables have been previously reported to affect yogurt texture (Tamime & Robinson, 1991). Sample formulations (Table 1) were selected in order to get a set of yogurts with a range of different texture characteristics, based on previous studies (Ares et al., 2007), the usual formulation of yogurts commercialized in the Uruguayan market, and results from preliminary tests.

Yogurts were prepared using 8% commercial sugar and 2% powdered skimmed milk. The rest of the formulation consisted of gelatin, modified starch, skimmed pasteurized milk (0.1% fat content) or whole pasteurized milk (2.6% fat content), as shown in Table 1.

Yogurts were prepared using a Thermomix TM 31 (Vorwerk Mexico S. de R.L. de C.V., Mexico D.F., Mexico). The solid ingredients were mixed with the milk, previously heated to 50 °C. The dispersion was mixed for 1 min under gentle agitation (100 rpm), heated to 90 °C for 5 min and cooled to 42 °C. Then, the mix was placed in glass containers and inoculated with 1 mL of lactic cultures, prepared by dispersing lyophilized cultures (Yo-Mix 205 LYO 250 DCU, Danisco, France) in UHT skimmed milk to a concentration of 250 DCU per liter.

Fermentation was carried out in a temperature controlled oven at (42 ± 1) °C and stopped when the sample reached a pH of 4.55 (after 5–6 h, depending on the formulation). When the final pH was reached, the coagulum was broken by agitating each yogurt for 1 min using the Thermomix TM 31 at 100 rpm. After that, yogurts were placed in glass containers, cooled under agitation to 25 °C in a water bath at 5 °C, and then stored refrigerated (4–5 °C) for 24 h, prior to their evaluation.

2.1.2. Consumer testing

Consumers (n = 74) were recruited among students, professors and workers from the School of Chemistry (Universidad de la

Table 1
Formulation of the yogurts used in Study 1.

Sample	Milk fat content (%)	Concentration of modified starch (%)	Concentration of gelatin (%)
1	0.1	0	0
2	0.1	0	0.5
3	0.1	1	0
4	0.1	1	0.5
5	2.6	0	0
6	2.6	0	0.5
7	2.6	1	0
8	2.6	1	0.5