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Interpreting consumer preferences: physicohedonic and psychohedonic models yield different information in a coffee-flavored dairy beverage

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Abstract

Designed experiments provide product developers feedback on the relationship between formulation and consumer acceptability. While actionable, this approach typically assumes a simple psychophysical relationship between ingredient concentration and perceived intensity. This assumption may not be valid, especially in cases where perceptual interactions occur. Additional information can be gained by considering the liking-intensity function, as single ingredients can influence more than one perceptual attribute. Here, 20 coffee-flavored dairy beverages were formulated using a fractional mixture design that varied the amount of coffee extract, fluid milk, sucrose, and water. Overall liking (*liking*) was assessed by 388 consumers using an incomplete block design (4 out of 20 prototypes) to limit fatigue; all participants also rated the samples for intensity of coffee flavor *(coffee)*, milk flavor *(milk)*, sweetness *(sweetness)* and thickness *(thickness)*. Across product means, the concentration variables explained 52% of the variance in *liking* in main effects multiple regression. The amount of sucrose ($\beta = 0.46$) and milk ($\beta = 0.46$) contributed significantly to the model (p's <0.02) while coffee extract ($\beta = -0.17$; $p = 0.35$) did not. A comparable model based on the perceived intensity explained 63% of the variance in mean *liking*; *sweetness* ($\beta = 0.53$) and *milk* ($\beta = 0.69$) contributed significantly to the model (p's <0.04), while the influence of *coffee* flavor ($\beta = 0.48$) was positive but marginally ($p = 0.09$). Since a strong linear relationship existed between coffee extract concentration and coffee flavor, this discrepancy between the two models was unexpected, and probably indicates that adding more coffee extract also adds a negative attribute, *e.g.* too much bitterness. In summary, modeling liking as a function of both perceived intensity and physical concentration provides a richer interpretation of consumer data.

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Keywords

Optimization; consumer insight; physicohedonic model; psychohedonic model; psychophysical model; coffee milk

1. Introduction

Optimization is an efficient and practical tool for product developers (Ares, Varela, Rado, & Gimenez, 2011; Dutcosky, Grossmann, Silva, & Welsch, 2006) to achieve a competitive product in the market (Stone & Sidel, 2004; Villegas, Tarrega, Carbonell, & Costell, 2010). Not only can an optimization technique define an optimal product (Dutcosky et al., 2006), but also help evaluate effects of independent variables on the response variables. Traditionally optimization techniques have been widely used in engineering. For example, response surface methodology (RSM) has been used to explore the optimal roasting temperature and time in terms of yield, levels of free sugar, phenolic compounds, antioxidant activity, and sensory preference for a coffee-like beverage from maize kernels (Youn & Chung, 2012). In the current marketplace consumers are more influential in the product value chain and play an important role in the process of new product development (Costa & Jongen, 2006). Thus, it is important to integrate consumer insights into each step of product development (Brunso & Grunert, 2007).

Product sensory properties directly influence consumer preferences and purchases (Mitchell, Brunton, & Wilkinson, 2009). The concepts and techniques of optimization, such as response surface methodology (RSM) (Modha & Pal, 2011), Euclidian distance ideal point mapping (EDIPM) (Meullenet, Lovely, Threlfall, Morris, & Striegler, 2008), preference mapping techniques (Greenhoff & MacFie, 1999), and Landscape Segment Analysis (LSA®, IFPrograms), have been applied in sensory science to explore consumer-defined optimal product characteristics. Here we employed a fractional, constrained mixture design for formulation and an incomplete block design for sensory analysis using untrained consumers.

Three distinct models are useful to properly integrate consumer insights into product development: physicohedonic (concentration-liking) models, psychophysical (concentration-sensation) models, and psychohedonic (sensation-liking) models. Each model provides unique insights and meaningful feedback for product development. Physicohedonic and psychohedonic models are of more interest to product developers due to their ability to offer directional solutions to questions of formulation, while psychophysical models offer insights into the relationship of physicohedonic and psychohedonic models.

Physicohedonic models are based on design variables (*i.e.*, formulation) and consumer acceptability (*i.e.*, liking). For example, consumer liking was modeled as a function of formulation to identify an optimal blended wine using a mixture design (Dooley, Threlfall, & Meullenet, 2012). Using this approach, the influence of design variables on response variables can be investigated, and optimal products can be described in terms of design variables. From the product developer's perspective, the physicohedonic models provide a practical and actionable solution; helping to determine which design variables are critical and how the product can be improved. However, this approach may be an oversimplification, as it assumes a simple relationship between concentration and sensation. Critically, this assumption may not be valid (Keast & Hayes, 2011), especially in cases where perceptual interactions may occur, when individuals perceive similar intensities from different physical concentrations, or when a single ingredient may contribute more than one sensory attribute. For example, adding more coffee extract into a coffee-flavored beverage might increase coffee flavor, which is assumed to be a positive factor for consumer acceptance, but may also increase bitterness that may be detrimental to consumer liking (Moskowitz & Gofman, 2007). The third case is seen for many non-nutritive sweeteners; in the asymptotic portion of the sweetness dose response curve, adding more acesulfame-K does not increase sweetness, but does increase bitterness (Schiffman, Booth, Losee, Pecore, & Warwick, 1995). In addition to changes in the intensity of a sensory response, the nature of the sensory property might be perceived differently with increase in concentration. For example, at a low titanium dioxide level, cheese looked opaque, but turned too white when extra titanium dioxide was added (Wadhwani & McMahon, 2012). The relationship between concentration and attribute sensory intensity is not normally linear (Hough, Sanchez, Barbieri, & Martinez, 1997).

In contrast, psychohedonic models link consumer acceptability to the perception of a product's sensory attributes (Greenhoff & MacFie, 1999; Meullenet et al., 2008). Fundamentally, psychohedonic models are meaningful and important (Keast & Hayes, 2011), because they can give direct feedback about factors driving consumer acceptance based on their sensory impact (Lovely & Meullenet, 2009). However, psychohedonic models may be less actionable. First of all, interactions between sensory properties are common (Hayes & Duffy, 2007;Wadhwani & McMahon, 2012; Xiong & Meullenet, 2006). Consequently, changes in one attribute might influence the perception of other properties (Hayes, Sullivan, & Duffy, 2010). Second, whatever findings are achieved from a psychohedonic model, further action on the product would typically be carried out by altering the formulation. Additionally, a sensory perception might be a function of multiple chemical components or design variables, e.g. adding either more milk or sucrose into a dairy-based beverage increases its thickness. As a result, the psychohedonic model may not directly indicate a workable solution for product improvement. Given that sensation (perceived intensity) is an intermediate variable between formulation and liking, we would expect sensation to be a better predictor of liking than concentration; indeed, perceived sweetness and creaminess are better predictors of liking than fat and sucrose concentration (Hayes & Duffy, 2008).

The objective of creating either physicohedonic or psychohedonic models is an understanding of consumer needs. Psychophysical models are useful for understanding and explaining conflicting information from physicohedonic and psychohedonic models during product development. To increase the likelihood of creating a successful product, it may be advantageous to study a two-stage concentration-sensation-liking model in addition to the simpler concentrationliking model. The present study was originally designed to optimize formulation of a new beverage (a coffee-flavored milk) for retail sale in a campus facility. Here, we explore the insight gained from moving beyond a physicohedonic model to a multipart model that considers psychophysical and psychohedonic relationships separately.

2. Materials and Methods

Participants were randomly assigned to one of three research conditions (described below). All the participants rated overall liking *(liking)* as well as the intensity of sweetness (*sweetness*), coffee flavor (*coffee*), milk flavor (*milk*), and thickness (*thickness*).

2.1 Ethics statement

Procedures were exempted from IRB review by the Penn State Office of Research Protections staff under the wholesome foods exemption in 45 CFR 46.101(b)(6). Participants provided informed consent and were compensated for their time.

2.2 Subjects

A total of 388 participants (110 men) were recruited ahead of time using an existing participant database maintained by the Sensory Evaluation Center at Penn State, or via staff intercepts in public spaces in and around the Food Science Department at Penn State.

To qualify for participation, individuals had to indicate they drank coffee or coffee-flavored beverages regularly (Table 1), and did not have any food allergies. About 40% of the consumers (n=155) were between 18–27 years old, 72 were 28–37, 56 were 38–47, 75 were 48–57, 26 were 58–67, and only 4 were over 67 years old. The majority (~77%) were White (n=298), while 59 identified themselves as Asian or Pacific Islanders, 9 as African or African American, and 11 did not report a race.

2.3 Sample formulation and preparation

Twenty coffee-flavored dairy beverages were formulated using a fractional mixture design with four constrained variables: coffee extract (3.0–5.0 wt %; Autocrat Sumatra 1397, Autocrat Natural Ingredients, Lincoln, RI), sucrose (5.0–8.0 wt %), milk (35–55 wt %, 2% fat, Berkey Creamery, University Park, PA), and water (35–55 wt %). These components accounted for 99.8% of the individual formulations. A constant amount of pectin (0.2 wt %; Grinsted® SY, Dupont Danisco) was added to all the samples. The exact composition of each formula is shown in Table 2. Pectin solutions were first prepared by blending pectin into the water. Coffee extract, milk, and sucrose were added to pectin solutions.

Batches were heated to 72 °C to assure that the sucrose was completely dissolved, the pectin dispersed, and the product was safe for consumption. The finished samples were kept at refrigeration temperature (~4°C) for at least 24 hours before serving. Two ounces of the coffee milk were served in 4-oz Solo transparent plastic cups (Solo Cup Company, Urbana, IL).

2.4 Product testing

Data were collected using Compusense *five*® (Compusense Inc., Guelph, ON, Canada) software. Participants were randomized to 1 of 3 test conditions upon entering test booths. In method I (n=127), only *liking* and attribute intensities were collected. In method II (n=129), participants rated *liking*, attribute intensities, and their ideal attribute intensities on separate, appropriately-worded line scales. In method III (n=132), *liking* was collected, and attribute appropriateness was assessed with just-about-right (JAR) scales. The ideal intensity and JAR data were not used here and will be reported elsewhere.

Liking was assessed using a standard 9-point hedonic scale (1 = "Dislike Extremely", 5 = "Neither Like Nor Dislike", and 9 = "Like Extremely") (Peryam & Pilgrim, 1957). Attribute intensities, both perceived and ideal, were measured using continuous line scales (0–100); two descriptive anchors were placed on 10% and 90% of these scales, representing low intensity (*e.g.*, "Not At All Sweet") and high intensity (*e.g.*, "Extremely Sweet"). Just-about-right (JAR) scales were designed as continuous line scales with three descriptive anchors, low intensity (*i.e.*, "Much Too Weak") on the left end, "Just About Right" at the middle, and high intensity (*i.e.*, "Much Too Strong") on the right end. Demographics and consumption behavior for coffee-based beverages were collected at the end of the session, after all sample evaluations.

To minimize fatigue, participants received 4 formulas out of 20 in an incomplete block design. The samples were served in a monadic sequential order, with a two-minute mandatory break between samples. During the break, participants were asked to rinse with room temperature (22°C) filtered water to reduce potential carry-over effects (Macfie, Bratchell, Greenhoff, & Vallis, 1989).

2.5 Statistical analyses

Data were analyzed using JMP® version 9.02 (SAS Institute Inc.). Analysis of variance (ANOVA) was conducted to detect effects of test conditions (method), product, and their interaction on *liking*. In the ANOVA model, panelist was a random variable nested within the method factor; method, product and their interaction were treated as fixed effects. Similar to multiple linear optimization models reported in the field (Johnson & Vickers, 1988; Schutz, 1983; Stone & Sidel, 2004), two linear regression models were fitted to diagnose and compare effects of formulation variables (sucrose, milk and coffee extract) and perceived attribute intensities on *liking*, *i.e.*, a physicohedonic (formulation-liking) model and psychohedonic (intensity-liking) model. In these two models, means of liking and intensity data were regressed using JMP®. Similarly, attribute intensities were regressed on formulation variables using multiple linear regression in JMP®.

3. Results

3.1 Influence of research method on *liking*

To justify aggregation of the data, the effect of research method on *liking* was determined. In the ANOVA model, 52% of the variance in *liking* was explained by product (*i.e.* formulation), method, and participant. As expected, *liking* differed as a function of product ($F_{19,1300} = 8.66$, $p<0.0001$). The effect of method on *liking* was not significant ($F_{2,374.5} = 0.75$, p-value=0.47), nor was the product by test method interaction ($F_{38,1297} = 1.33$, $p=0.09$), indicating there was no systematic difference in *liking* resulting from the test methods. Therefore, *liking* data were combined across methods for the remaining analyses.

3.2 Effect of formulation on *liking*

In the physicohedonic model, concentration variables (amount of coffee extract, milk, and sucrose) explained 52% of the variance in *liking* in main effects multiple regression (fitted model: *liking* = 4.0+2.8**milk*−10.3**coffee*+17.6**sucrose*, p=0.008). The amount of sucrose (β = 0.46) and milk (β = 0.46) contributed significantly to the model (p's <0.02) while coffee extract (β = −0.17) did not (p = 0.35). The amount of sucrose and milk were equally important to *liking* in this model. Although not significant, greater amounts of coffee extract seemed to negatively influence *liking*.

3.3 Relationship between formulation and perceived intensity

Attribute intensities (*sweetness*, *milk*, *coffee* and *thickness*) were regressed on the concentrations of formulation variables (*i.e.*, sucrose, milk, coffee extract and total solids) using multiple linear regression models and effects graphs are presented in Figure 1. *Sweetness* was influenced by the concentrations of sucrose (β = 0.84, p<0.0001), coffee extract (β = −0.27, p<0.002), and milk (β = 0.22, p<0.007) (p<0.0001, r^2 = 0.94), with no significant interaction between variables (p>0.05). *Coffee* flavor was dominated by the concentration of coffee extract (β = 0.95, p<0.0001), but the effect of milk concentration, though smaller (β = −0.16), was significant (p<0.01) (p<0.0001, r^2 = 0.96). Again there were no significant interactions (p>0.05). Somewhat surprisingly, *milk* flavor was influenced most by coffee extract concentration (β = −0.72, p<0.0001), followed by milk concentration (β = 0.52, p<0.0002) (p<0.0001, r^2 = 0.87), with no significant interactions (p>0.05). Apparently the strong flavor of coffee masked the more subtle dairy flavor. *Thickness* was significantly influenced by milk (β = 0.64, p<0.0007) and sucrose concentration (β = 0.45, p<0.0110) (p=0.0045, r^2=0.72), largely through their effect on total solids content (Figure 2).

3.4 Effects of perceived attribute intensities on *liking*

The psychohedonic (sensation-liking) model based on perceived intensity (*sweetness*, *milk* and *coffee*), explained 63% of the variance in *liking* (fitted model: *liking* = 0.03+0.06**milk* +0.03**coffee*+0.03**sweetness*, p=0.001). *Sweetness* (β = 0.53) and *milk* (β = 0.69) contributed significantly to the model (p's <0.04), while *coffee* (β = 0.48) was marginal (p =0.09).

4. Discussion

Previous studies have demonstrated that overall liking scores can be influenced by the inclusion of attribute diagnostic questions on the ballot. Popper, Rosenstock, Schraidt, and Kroll (2004) found that asking participants to rate attribute intensities using JAR scales influenced the average ratings of overall liking, but intensity scales had no such effect. The presence of attribute JAR ratings could increase or decrease the ratings for overall liking (Earthy, MacFie, & Hedderley, 1997). In contrast, attribute intensity rating did not show a significant effect on overall liking (Mela, 1989; Vickers, Christensen, Fahrenholtz, & Gengler, 1993). Based on this, we anticipated that the method used to rate attributes (intensity scales, ideal scaling or JAR scaling) would influence the overall *liking*, but we found no such effect.

In contrast to the physicohedonic (formulation) model where the influence of milk and sucrose were equivalent, *milk* had a larger influence on *liking* than did *sweetness* in the psychohedonic model. More critically, the direction of the effect for *coffee* flavor was opposite that of coffee extract. That is, more *coffee* flavor resulted in greater liking, whereas in the physicohedonic model, more coffee extract either had no effect, or may have even reduced liking slightly. Informal tasting revealed that more coffee extract increased bitterness in addition to *coffee* flavor. However, we failed to ask consumers to rate bitterness as an attribute, and we are thus unable to formally model its effect on liking statistically. However, Boeneke, McGregor, and Aryana (2007) reported that increasing coffee flavor was accompanied by an increase in bitterness of roasted coffee as assessed by a trained panel, and Moskowitz and Gofman (2007) reported consumer liking of coffee increased with the intensity of its bitterness to a maximum, beyond which liking declined. Furthermore, we observed a reduction in *sweetness* with increasing concentrations of coffee extract (Figure 1b) as would be expected from suppression of sweetness by bitterness (Lawless, 1979).

In the present case it is likely that *coffee* flavor was perceived as more than just bitterness, or a percept other than bitterness, since *liking* was positively related to *coffee* flavor but negatively related to the amount of coffee extract. This is a subtle, but important, distinction, for if a product developer could increase *coffee* flavor, say through the introduction of key aroma compounds, without a coincident increase in bitterness (as comes with simply adding more coffee extract), then the two percepts could be optimized separately.

The psychohedonic model explained more variance in *liking* than the physicohedonic model, consistent with prior results (Hayes & Duffy, 2008). That perceived intensities are better predictors of *liking* than formulation is entirely expected, as perceived intensity is presumed to mediate the relationship between concentration and *liking*. Milk concentration has been shown to affect the optimal sucrose concentration in coffee (Moskowitz, 1985), and the interaction between milk and coffee flavor (Parat-Wilhelms et al., 2005) was critical to consumer acceptance of a coffee milk beverage (Boeneke et al., 2007). In the present case, our coffee-flavored dairy beverage is a complex food matrix, where perceptual and physical interactions among stimuli are quite common. Adding more sucrose might be expected to reduce the bitterness of coffee (Pangborn, 1982) via mixture suppression that occurs centrally (Lawless, 1979), whereas adding milk fat may alter bitterness via partitioning (see Bennett, Zhou & Hayes, 2012). Previously, Lawless (1977) observed non-intuitive perceptual interactions when attempting to predict liking from stimulus concentration in simple mixtures: adding a small amount of quinine (which is unpleasant by itself) counterinuitively increases liking for a sweet-bitter mixture by reducing excessive sweetness. Here, we confirm similar complex interactions and extend them beyond model systems to a real food product.

5. Conclusions

A psychohedonic (intensity-liking) model is better than physicohedonic (formulation-liking) model for predicting consumer liking. However, a physicohedonic model might be more actionable from a product formulation perspective. Product developers and sensory specialists should always remember that a single ingredient may influence more than one perceptual attribute, especially in a complex food. Unlike some pure compounds, *e.g*. sucrose, which might uniquely produce a single *sweetness* perception, adding more coffee extract not only increases coffee flavor but also bitterness. Psychophysical models can help in understanding and interpreting the results from physicohedonic and psychohedonic models.

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Highlights

- Consumer insights have a critical role in the process of product development.
- A psychohedonic model was better than physicohedonic model for predicting liking.
- Psychophysical models help to interpret physicohedonic and psychohedonic models.
- Consumer preference is better understood by considering all models simultaneously.
- Coffee extract is a complex ingredient producing several sensory perceptions.

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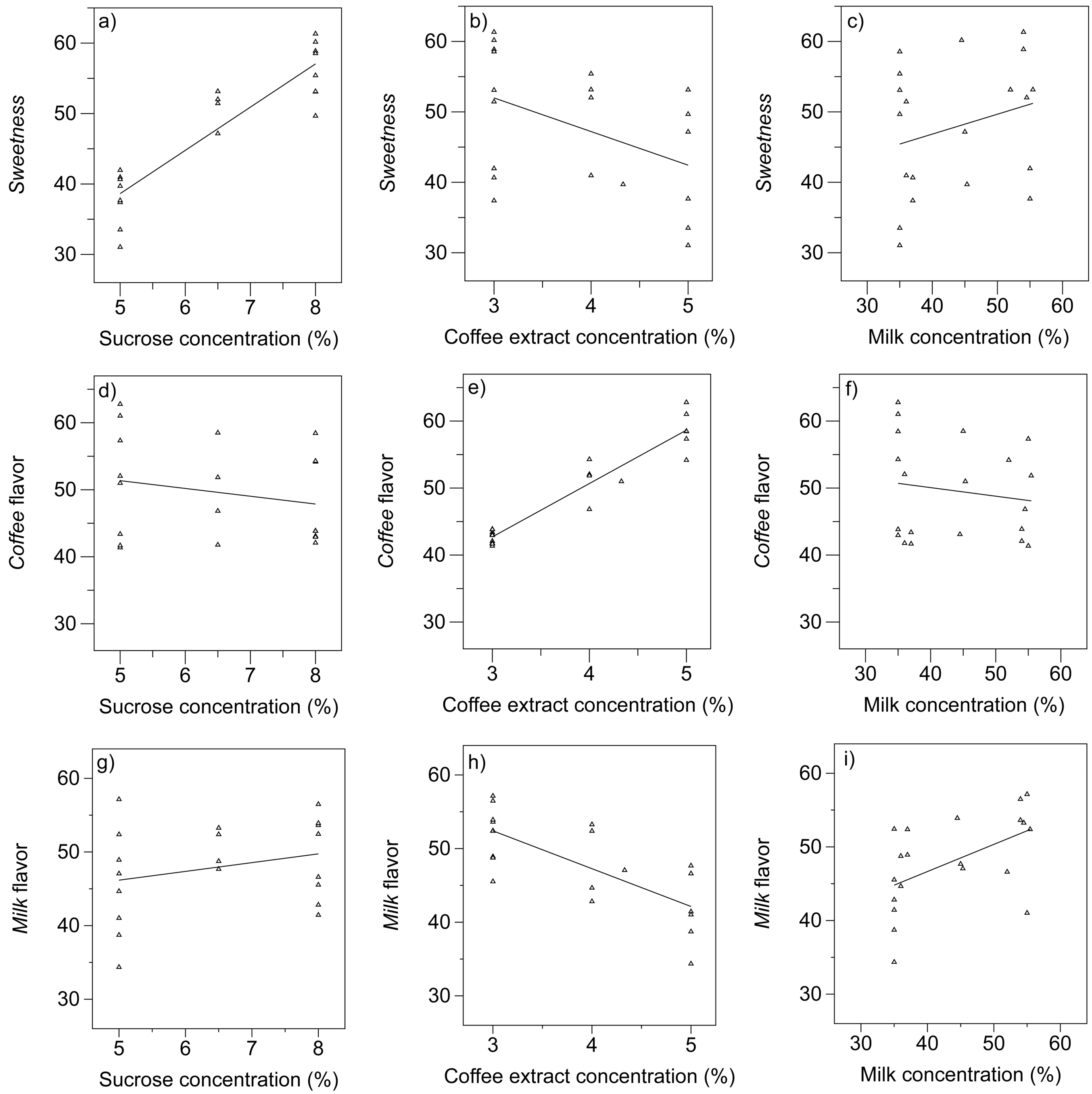

Figure 1.

Effects graphs for psychophysical models. *Sweetness* (a,b,c), *coffee* (d,e,f) and *milk* (g,h,i) as a function of sucrose (a,d,g), coffee extract (b,e,h) and milk (c,f,i) concentrations.

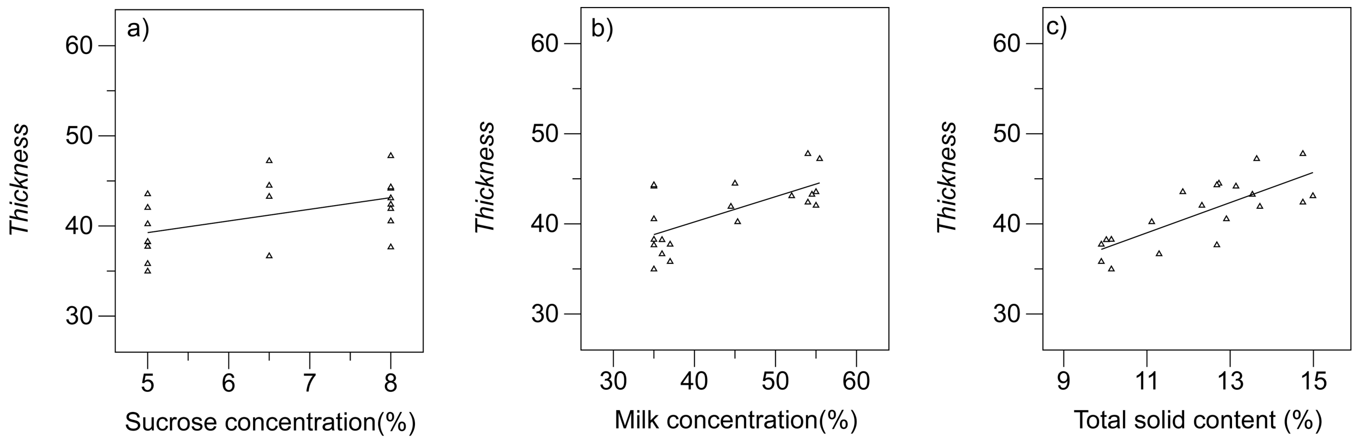

Figure 2.

Effects graphs for *thickness* as a function of sucrose (a) and milk (b) concentrations and total solids content of the beverages (c).

Table 1

Regularly consumed coffee-flavored products

Products	**Frequency (%**
Cappuccino	23.7
Latte	31.4
Black coffee	25.0
Iced coffee	32.4
Coffee with milk, cream, and/or sucrose	60.0

Table 2

Sample formulations (in weight percentage)

Product[1]	**Milk (%)**	**Water (%)**	**Coffee extract (%)**	**Sucrose (%)**	**Solid content (%)**[2]
1	35.93	54.89	3.99	4.99	10.02
2	45.24	45.24	4.32	4.99	11.11
3, 19	36.93	54.89	2.99	4.99	9.90
4, 9	53.89	34.93	2.99	7.98	14.75
5	34.93	51.90	4.99	7.98	13.14
6, 18	34.93	54.89	4.99	4.99	10.15
7	44.91	43.41	4.99	6.49	12.73
8	35.93	54.39	2.99	6.49	11.29
10	54.89	34.93	4.99	4.99	12.32
11	44.41	44.41	2.99	7.98	13.71
12, 16	54.39	34.93	3.99	6.49	13.53
13	54.89	36.93	2.99	4.99	11.86
14, 17	34.93	53.89	2.99	7.98	12.68
15	51.90	34.93	4.99	7.98	14.99
20	34.93	52.89	3.99	7.98	12.91

[1]Samples in the same row share the same formulation.

[2]Calculated from the solids content of the ingredients.