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Development of a Methodology for Predicting Consumer Acceptance and Preference Toward Beverages

Shilpa Shailesh Samant
University of Arkansas, Fayetteville

Development of a Methodology for Predicting Consumer Acceptance and Preference Toward Beverages

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Shilpa Shailesh Samant
Institute of Chemical Technology
Bachelor of Technology in Food Engineering and Technology, 2013
University of Arkansas
Master of Science in Food Science, 2015

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University of Arkansas

This dissertation is approved for recommendation to the Graduate Council.

Han-Seok Seo, Ph.D.
Dissertation Director

Jean-Francois Meullenet, Ph.D.
Committee Member

Philip G. Crandall, Ph.D.
Committee Member

Andronikos Mauromoustakos, Ph.D.
Committee Member

Matthew Feldner, Ph.D.
Committee Member

ABSTRACT

Consumer behavior toward food/beverages is influenced by multisensory attribute perceptions as well as emotional experiences. Traditional methods of sensory testing lack the ability to capture emotional responses and as a result, measuring food/beverage-evoked emotions remains a research challenge. There were three objectives of this dissertation study. Firstly, this study aimed to develop prediction models of acceptance of and preference for basic taste solutions using sensory attribute intensities and emotional responses. Secondly, this study aimed to extend the findings of the first objective to develop prediction models of commercially-available vegetable juice products in terms of (a) acceptance and preference under blind-tasting conditions and (b) purchase behavior under informed-tasting conditions. Lastly, this study aimed to determine the influence of individual personality traits on the prediction models of acceptance and preference for basic taste solutions. Combination of explicit measures (self-reported emotions) and implicit measures (facial expressions and autonomic nervous system responses) were used to measure beverage-evoked emotions. Findings from this study suggest that combination of explicit and implicit emotional measures along with sensory attribute intensities can better predict acceptance of and preference toward basic taste solutions or vegetable juice products as compared to individual variables. In addition, combination of sensory attribute intensities and emotional responses along with non-sensory factors provided optimal prediction model of purchase behavior. Finally, individual differences such as personality traits, specifically those associated with extraversion and neuroticism, have potential to influence the prediction models developed to predict consumer behavior. In conclusion, this dissertation study recommends the combined use of explicit and implicit emotional measures, in addition to sensory and/or non-sensory cues, to predict consumer behavior in terms of acceptance, preference, and purchase-related decisions. In addition, it is important to consider individual differences such as personality traits of participants when developing prediction models of consumer behavior using sensory intensities and emotional responses. This dissertation study provides valuable and practical information for better understanding of consumer behavior to sensory scientists, applied-emotion researchers, and food manufacturers.

Keywords: Consumer behavior, Emotion, Self-reported, Facial expressions, Autonomic nervous system response, Sensory perception

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DEDICATION

Dear Mom and Dad,
This is all because of you. Thank you!

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CHAPTER 1

GENERAL INTRODUCTION

Understanding consumer behavior is exceedingly important for sensory scientists and market researchers to understand potential market success of any new food product. Traditional methods to asses consumer behavior are affective tests including acceptance rating as well as preference ranking tests that measure liking and choice, respectively (Meilgaard, Civille, & Carr, 2015, Chap. 12). It is common that researchers integrate sensory attribute perception cues such as taste, flavor and aroma intensities to holistically understand quality and drivers of product liking using traditional methods. Previous research suggests that sensory attribute perception might not be a clear indicator of consumer acceptance and preference due to lack of direct relationship between sensory intensities and liking of the product (Stolzenbach, Bredie, Christensen, & Byrne, 2016). To better understand consumer behavior, a clear understanding of all elements associated with the term "behavior" becomes essential which includes liking traits, preferences and purchase intentions. According to Kardes, Cronley, and Cline (2010) consumer activities such as liking toward a product are driven by their emotional, mental and behavioral responses. Considering specifically food products, in addition to complex cognitive processing of multisensory perceptions (e.g., flavor and taste), consumer behaviors are strongly driven by emotional experiences in response to what they eat or drink (Berridge, 1996; Hirschman & Holbrook, 1982). In other words, the emotional response experienced by a consumer toward a food/beverage plays an important role in determining his/her liking of or preference for a product. In fact, emotional responses toward a food or beverage item also impact their purchase behavior toward the product (Songa, Slabbinck, Vermeir, & Russo, 2019). Traditional methods of sensory testing have been primarily developed to measure multisensory perception but lack the ability to capture emotional experience of the consumer.

The past decade has seen a surge in interest to study food/beverage-evoked emotions which could be defined as "*a brief but intense physiological and/or mental reaction to a food* *or beverage item*” (Bagozzi, Gopinath, & Nyer, 1999; Kenney & Adhikari, 2016; King & Meiselman, 2010; Samant, Chapko & Seo, 2017). In fact, Kaneko, Toet, Brouwer, Kallen, and van Erp (2018) report that the number of research publications in the field of food-evoked emotions more than doubled in the years 2013-2016 as compared to years 2009-2012. Recent studies show that food/beverage-evoked emotions are related to either consumer acceptance or preference toward food/beverage products such as basic taste solutions (Samant et al., 2017), breakfast drinks (de Wijk, He, Mensink, Verhoeven, & De Graaf, 2014), squashes (Ng, Chaya & Hort, 2013), fruit and vegetable juices (Waehrens, Grønbeck, Olsen, & Byrne, 2018), coffee and tea (Pramudya & Seo, 2018). In general, better-liked products evoke positive emotions (e.g., happy, calm, joyful) whereas lesser-liked products evoke negative emotions (e.g., disgusted, bored) among participants. Interestingly, Gutjar et al. (2015) suggest emotional responses along with liking ratings better explain choice behavior among consumers compared to liking ratings along. Therefore, it is evident that food/beverage-evoked emotions can be used as tools to understand the different dimensions of consumer behavior.

The most challenging aspect of this kind of applied-emotion research is measurement of food/beverage-evoked emotions. Different methodologies that have been explored and developed in the past could be classified into two major types, namely, explicit (or “direct”) and implicit (or “indirect”) methods. Explicit methods, including self-reported ratings on questionnaires (e.g., EsSense Profile®; King &; Meiselman, 2010), are most popularly used among researchers to measure food/beverage-evoked emotions due to their simplicity, ease-of-use and relatively straightforward statistical data processing (Kaneko, et al. 2018; Lagast, Gellynck, Schouteten, De Herdt, & De Steur, 2017). However, explicit methods rely on accuracy of translation of emotions from experience to expression using the descriptor term. In other words, the participant has to correctly self-report his/her emotional experience. This could lead to some loss of information. Implicit methods, including facial expression (FE) analysis and autonomic nervous system (ANS) response analysis, are more involuntary and do not require participants to retrospect their experience. However, implicit measures can be complex in terms of execution and data processing (Lagast et al., 2017). Specifically, FE is typically carried out using a relevant computer software with inbuilt information correlating changes in human facial expression to specific emotions (Tian, Kanade, & Cohn, 2005). ANS responses are also considered implicit methods of emotional measurement based on the theory that emotional experiences are manifested into physiological changes in the human body (Kreibig, 2010). These changes are mainly observed in ANS responses such as electro-dermal activity (EDA) of the skin measured as skin conductance response (SCR), cardiovascular activity measured as heart rate (HR), and skin temperature (ST) (Kenney & Adhikari, 2016; Kreibig, 2010). Lagast et al. (2017) explored the use of explicit and implicit methods to measure food-evoked emotions from early 2000s to 2016. The authors reviewed 70 articles and reported that 52 out of 70 articles (74.3%) used explicit methods, 12 (17.1%) used implicit methods and only 6 (8.6%) used a combination of explicit and implicit methods.

Previous studies have attempted to explore the relationship between food/beverage-evoked emotional responses, acceptability and sensory perception of the food/beverage products (Crist et al., 2018; Desmet & Schifferstein, 2008; Lagast et al., 2017; Rousmans, Robin, Dittmar, & Vernet-Maury, 2000). It is possible that among the different sensory modalities, smell and taste might have the strongest impact on food-evoked emotions (Desmet & Schifferstein, 2008). A recent study by Crist et al. (2018) measured facial expressions toward different concentrations of bitter-tasting solutions. It was found that bitter-tasting solutions can elicit more disgust emotion compared to water as control. Another study by Rousmans et al. (2000) measured food-evoked emotions using five ANS physiological measures (skin potential, skin resistance, skin blood flow, skin temperature, instantaneous heart rate). Specifically, subjects were given primary taste solutions (sweet, bitter, salty, and sour) at concentrations with proven taste recognition. Findings from this study show that skin resistance and heart rate were affected the most in response to taste qualities of the samples. A study in Netherlands by de Wijk et al. (2014) evaluated the facial expressions and ANS parameters such as heart rate, skin conductance response and skin temperature of five commercially available breakfast drinks. Participants' hedonic impression and intensities ratings were also recorded. Results showed that higher liking of the drinks was associated with increased heart rate and skin temperature. In addition, increased intensities of the drinks were associated with reduced heart rate, skin temperature and more neutral or negative emotions. Going beyond liking and preference, some researchers have also explored use of emotional responses to understand purchase behavior (Songa et al., 2019). Songa et al. (2019) suggest that emotional reactions measured using facial expressions toward sustainability logos on different food products might provide valuable information to understand purchase intent of the consumers. Results from these studies open doors to the possibility of integrating sensory perception and emotional responses to better understand and predict liking, preference, and even purchase behavior toward food/beverage product.

As mentioned earlier, applied-emotion research is relatively new to the field of sensory and consumer sciences. There is a knowledge gap with respect to the association between food/beverage-evoked emotions and consumer behavior. Firstly, it is still unclear which of the individual methods or combination of methods developed to measure emotional responses work best to understand consumer acceptability, preference and purchase behavior. Secondly, integration of sensory perception cues along with emotional responses to determine consumer behavior is relatively unexplored. Thirdly, research on individual differences in food/beverage-evoked emotional responses due to non-sensory context (e.g., different personality traits among consumers) is scarce. Lastly, very few research studies dive into testing the reliability of association between emotional responses and consumer behavior. In an attempt to address the above limitations, the main objective of this study was to develop a novel methodology to predict consumer behavior. Specifically, the study developed prediction models for consumer behavioral aspects such as of acceptance (liking) and preference (choice) toward basic taste solutions using sensory intensity perceptions and emotional responses measured by a combination of self-reported emotions, facial expressions, and ANS responses. Moreover, the study explored the effect of non-sensory factors such as consumers' individual personality traits on the association between emotional responses and consumer acceptability. Finally, the study extended its findings to predict liking, preference and purchase behavior toward commercial vegetable juice products using emotional responses and sensory perception cues. Test samples from this study were chosen to be beverage products to avoid any bias due to unwanted facial movement that are generally encountered during chewing of solid food. This is the first study to develop a prediction model of consumers' behavior toward beverages using combination of explicit and implicit emotional responses along with sensory attribute perceptions as independent variables (Lagast et al., 2017).

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CHAPTER 2

LITERATURE REVIEW

1. Consumer acceptability and preference

1.1. Concept

Consumer behavior, according to Kardes, Cronley, and Cline (2010) involves the complex mixture of consumer activities that ultimately lead to the decision of buying a product. These activities might include how much a consumer likes a product, whether he/she prefers it over other similar products and their overall intention to purchase that product. Consumer liking is a broad concept including acceptability for a product, such as food or beverage, and is commonly measured using hedonic responses in sensory sciences. The term "hedonic" is derived from the Greek word "*hedon*" meaning pleasure. Thereby, hedonic responses or acceptability of a food/beverages provide information about pleasure derived from oro-sensory stimulation (Mela, 2006). Therefore, hedonic or acceptance testing is performed to answer questions such as "*how much to do you like this product?*" and "*how acceptable you think this product is"?* (Meilgaard et al., 2015). Common acceptability testing measures such as hedonic responses generally yield continuous data. In addition to understanding acceptability, researchers are often interested to answer the question *"which product do consumers like best?"* In such scenarios, acceptability tests are paired with choice-based preference approach. Preference measures yield choice data which is generally ordinal in nature. Common preference measures include paired- or multiple-ranking tests wherein participants are asked to rank the products in order of their preference (Meilgaard et al., 2015). Purchase intent of a consumer could be gauged by subjectively asking him/her their likelihood of buying the product (Meilgaard et al., 2015; Samant & Seo, 2016a) or through indirect measures assessing willingness to pay for a product (Van Loo et al., 2015). Subjective ratings of purchase intent are generally considered as a part of acceptance testing (Meilgaard et al., 2015).

1.2. Factors influencing consumer acceptability and preference

Early literature regarding acceptability and preference toward food/beverages was exclusively dependent on sensory parameters such as appearance, taste, aroma, texture and flavor (Sclafami, 1991). For instance, sweet taste is perceived as pleasant to humans, whereas bitter taste is considered unpleasant. Aromas such as citrus and rose are generally considered pleasant whereas putrid odors such as rotten eggs are considered unpleasant. Moreover, intensity of the attribute can also affect hedonic responses (Stolzenbach, Bredie, Christensen, & Byrne, 2016; Samant, Chapko & Seo, 2017). The relationship between attribute intensities and liking is not consistent based on previous studies and depends on type of food as well as type of attribute being evaluated (Stolzenbach et al., 2017).

It is worth understanding that there are numerous factors, in addition to product-related characteristics that might impact the acceptance and preference toward the product. For instance, non-sensory attributes such as packaging label information including brand, price, ethics, origin, health benefits and nutrition label have a strong impact on product acceptance and liking (Cranage, Conklin, & Lambert, 2005; Samant & Seo, 2015; Songa, Slabbinck, Vermeir & Russo, 2019). These factors do not inherently correlate with sensorial properties of the food but have potential to create certain sensorial expectations in the mind of consumers (Fernqvist & Ekelund, 2014; Samant & Seo, 2016b; Solheim, 1992). For instance, Solheim (1992) asked consumers to rate their overall liking of reduced-fat sausages under two conditions: 1) they were told that the product contained normal fat content (20%) and 2) they were told that the product contained reduced fat content (12%). Even though the product tasted by the participants in both conditions was the same (reduced-fat sausage), higher-fat content information led panelist to like the product better and consider it more tasteful compared to when provided with low-fat information. In another study, Samant and Seo (2016b) reported that factors such as level of sustainability and processing label understanding could affect overall liking of chicken products. In particular, it was found that higher label understanding and awareness led to higher acceptability of chicken products compared to lower label understanding. Especially focusing on purchase intent, researchers have shown that providing label information (i.e., informed condition) provides a better idea about purchase behavior as compared to only tasting the sample, i.e., blind condition (Cranage et al., 2005; Kytö, Järveläinenb, & Mustonenc, 2018). Furthermore, context also plays an important role in influencing consumer behavior. For instance, a coffee might be more liked and preferred in a café as compared to laboratory conditions (Bangcuyo et al. , 2015). Bangcuyo et al. (2015) showed that consumer liking in virtual coffee house using immersive technologies was different and more predictive of future behavior as compared to liking reported by consumers in a laboratory setting.

In addition to non-sensory factors, human physiological, demographical and genetic differences also contribute to individual differences among consumers impacting their hedonic responses toward food/beverage. For instance, thiourea compounds such as 6-n-propylthiouracil (PROP) tastes bitter to some people whereas it is tasteless to others. This phenomenon is primarily due to genetic differences in presence/absence of taste buds expressing PROP-related receptors on the tongue (Snyder et al., 2006). Some studies show that consumers having higher sensitivity to PROP have lower liking and acceptance of bitter-tasting foods such as black coffee, dark breads and alcohol compared to those with lower sensitivity (Fischer, Griffin, England, & Garn, 1961). In fact, higher sensitivity to PROP can also result in lower acceptance of sweet and fatty foods (Duffy & Bartoshuk, 2000; Yeomans, Tepper, Rietzschel, & Prescott, 2007). In addition to PROP status, demographics such as gender, age and ethnicity also influence hedonic responses toward food/beverages. Some studies show that overall pleasantness of sweet taste is generally rated higher among males compared to females (Enns, Van Itallie, & Grinker, 1978; Laeng, Berridge, & Butter, 1993).

A possible reason is that since women are more weight-conscious than men, there might be a negative hedonic response to sweet taste. Another instance of gender-based hedonic difference was observed in a Norwegian behavioral study by Kubberod, Ueland, Tronstad, and Risvik (2002). These researchers found that women associate lower liking for meat with visible blood compared to men who like more red-colored meat. However, it is important to understand that demographic impact on hedonic responses is product-specific and it is difficult to derive a common relationship. Therefore, careful panel selection is extremely important when conducting consumer testing of food/beverages to avoid bias.

1.3. Measurement of consumer acceptability and preference

For more than five decades, the most popular and convenient method to measure acceptability has been scaling. Category scales are the most common scaling techniques. Scales having as many as twenty-one categories have been explored by sensory researchers (Meilgaard, 2015). However, the 9-point hedonic scale is most preferred and is extensively used for almost all food/beverages. It was initially developed in 1947 by Quartermaster Food and Container Institute for Armed Forces as an improved alternative to paired comparison methods for meal choices (Peryam & Pilgrim, 1957). It was further revised and the final version of 9-point hedonic scale was selected base on its reliability and discriminability by Peryam and Girardot (1952). The 9-point hedonic scale is a balanced bipolar scale with four positive and four negative categories along with a neutral center. Each category includes a verbal label descriptor with varying degrees of affect. The placement of the verbal descriptors are such that they are considered to be in continuum (Peryam & Pilgrim, 1957). It is one of the simplest scales to use for researchers as well as untrained consumers providing reliable hedonic information (Lim, 2011). There were some initial concerns among researchers regarding presentation format of the scale (vertical vs horizontal presentation) though recent studies suggest that presentation format has negligible effect on scale performance (Lim, 2011). However, there are certain limitations associated with the 9-point scale in terms of discriminability ability and statistical analysis. In order to overcome these limitations, line scales such as Visual Analogue scales (VAS) are used for hedonic measurement. However, use of line scales for hedonic response measurement is still limited (Methven, Jiménez-Pranteda, & Lawlor, 2016). Other scales developed to measure acceptability in terms of hedonic responses include Magnitude Estimation or ME (Steven, 1956, 1957), Labeled Affective Magnitude or LAM scale (Schutz & Cardello, 2001) and Labeled Hedonic Scale or LHS (Lim, Wood, & Green, 2009). These scales have been less explored as compared to the traditional 9-point hedonic scale. A common disadvantage of most of the scaling techniques is their reliance on verbal understanding of the descriptors.

Preferences are generally measured using ranking tests which include paired preference (choice of one sample over other) or rank preference (relative order of preference) (Meilgaard et al., 2015). It should be noted that ranking tests generally require re-tasting samples restricting the number of samples used for hedonic testing (Lim, 2011).

2. Sensory perception of food and beverages

2.1. Concept

Human senses involved in sensory perception of food/beverages include: 1) vision for appearance perception such as color, size, shape and clarity, 2) touch for texture perception, 3) olfaction for aroma perception, 4) trigeminal factors for perception of irritants such as pepper, menthol and ginger causing heat, burn, pungency, pain, 5) gustation for taste perception, and 6) hearing for auditory perception (Meilgaard et al., 2015). However, flavor attribute perception itself involves combination of olfactory, gustatory and trigeminal senses. Interestingly, it is not necessary that we perceive each attribute as a separate entity. In fact, some studies show that sensory perception is a multi-integrated perception of different sensory attributes with a high possibility of cross-modal interaction. In other words, one attribute affects perception of the other (Koza, Cilmi, Dolese, & Zellner 2005; Seo et al., 2010). Traditional sensory evaluation techniques aim at gaining insight about how consumers perceive different food/beverage attributes and is mainly focused on measurement of intensity perception. This information provides insights to food/beverage manufacturers about specific attributes driving liking of the product.

2.2. Factors influencing sensory perception

Sensory perception of food/beverage attributes is affected by various physiological, psychological and individual factors. One of the major physiological factors affecting sensory perception of food/beverage is adaptation (Meilgaard et al., 2015; O'Mahony, 1986). By definition, *adaptation is a decrease or change in sensitivity to a given stimulus as a result of continued exposure to that stimulus or a similar one*. For instance, sweetness perception of an aspartame-sweetened beverage will be higher when it is consumed after drinking water as compared to when it is consumed after drinking a sugar-sweetened beverage. This is because prior tasting of the sugar decreases sensitivity to sweetness (O'Mahony, 1986). Other physiological factors affecting sensory perception are enhancement (presence of one substance increasing perceived intensity of other) and suppression (presence of one substance decreasing perceived intensity of other). These factors are primarily dependent on the composition and sensory characteristics of food/beverage. Psychological factors affecting sensory perception are mainly termed as "errors" by Meilgaard et al. (2015). During sensory evaluation, participants may have pre-conceived ideas about a food/beverage thereby affecting their sensory perceptions. This type of error is called expectation error and is minimized by providing minimal information to the participants about the products prior to testing. In addition, number of samples and order of samples can also result in varied sensory perceptions. To avoid these errors during sensory testing, researchers ensure sample randomization and limit number of samples.

Individual differences perhaps have maximum effect on sensory perception of food/beverage. Health status, smoking habits and genetic factors have been reported to influence intensity perceptions. As mentioned earlier, genetic factors affect PROP sensitivity of a person thereby affecting their bitter taste perception (Snyder et al., 2006). To overcome this variability during sensory evaluations, researchers ensure careful panel selection.

2.3. Measurement of sensory perception

Similar to acceptability testing, scaling techniques are the most common approach to measure sensory attribute perception. These methods are focused on measuring how intensely one perceives the sensory attribute. Intensity scales can be category, line or magnitude estimation (ME) yielding ordinal, continuous and ratio data, respectively (Meilgaard, 2015). Category scales, such as Natick nine-point scale asks panelists to rate the intensity of the attribute from "very weak" to "very strong" (Bartoshuk et al., 1999). However, these are not often used in intensity perception owing to limited statistical analysis of ordinal data. Line scales, such as Visual Analogue Scale (VAS) or 15-cm line scales, are the most commonly used to measure intensity perception (Meilgaard et al., 2015). They are preferred over other scales since they are easy to use, provide information about the subtle differences between samples and allow relatively straightforward data handling and processing. However, product comparison might be difficult with line scales. As an improvement to line scales, ME scales were introduced yielding ratio data providing information about how strong/weak a sensory attribute is in one product compared to another. As mentioned earlier, ME scales lack semantic information to interpret the data analysis effectively. Therefore, Labeled Magnitude

Scale (LMS) or the “Green Scale” was introduced to provide semantic information about intensity perception in addition to yielding ratio data (Green et al., 1993). It is semantically labeled with “barely detectable” as the negative extreme and “strongest imaginable” as the positive extreme. The scale has quasi-logarithmic spacing between each label based on the assumption that human sensory intensity perception is not linearly related with stimuli concentration. However, LMS is restricted to oral stimuli and some researchers suggest that verbal descriptors used in the scale might not yield reliable results (Green Shaffer, & Gilmore, 1993). As a further improvement, general Labeled Magnitude Scale (gLMS) was introduced by Bartoshuk, Duffy, Fast, Green, and Snyder (2001) to measure intensity perception of different sensory modalities. This scale is suggested to encompass higher range of perceptions since the extreme labels are “No sensation” and “Strongest imaginable sensation of any kind”. Currently, gLMS is being widely used for sensory testing even though it requires rigorous panel training. Choice of scale depends on type of attribute and food or beverage being evaluated.

3. Emotional responses to food and beverages

3.1. Concept

The term “affect” is a broad concept encompassing a range of feelings people experience considering two similar yet relatively distinct phenomena, namely, mood states and emotions. Mood states are generally conceptualized to be longer lasting with weaker intensity mostly lacking a contextual stimulus. Emotions are more intense feelings that are in context or directed toward someone or something with an action-oriented outcome (Mauss & Robinson, 2009). In other words, one could describe emotions as “*tools by which we appraise experience and prepare to act on situations*” (Cole et al., 2004, p. 319). The scientific community is divided based on different emotion theories. Two of the common theories of emotion are discrete emotion theory and dimensional model of emotions. Discrete emotion theory describes emotions as a set of "basic" entities with distinct bodily manifestations whereas the dimensional theory proposes emotions can be explained by two or three dimensions (e.g., valence and arousal), instead of multiple monopolar dimensions (Izard, 2007). Based on discrete emotional theory, an emotion could be defined as "*a set of neural, bodily/expressive and feeling/motivational components generated rapidly, automatically and non-consciously when ongoing affective-cognitive processes interact with the sensing or perception of an ecologically valid stimulus to activate evolutionarily adapted neurobiological and mental processes"* (Izard, 2007). Extending this concept, food/beverage-evoked emotion could be defined as brief but intense physiological and/or mental reaction to a food or beverage item (Bagozzi et al., 1999; King & Meiselman, 2010; Kenney & Adhikari, 2016).

Early theories on the association between food consumption and emotional responses originated with respect to stress and anxiety. Specifically, it was found that stress and anxiety have potential to act as drivers of over-eating or binge eating with a consequence of reaching a calmer emotional state, especially in the obese population (Canetti, 2002). Later, a bi-directional association between food and emotion was reported meaning that in addition to different emotional states affecting food/beverage consumption, eating food can also evoke different emotional responses (Köster & Mojet, 2015). Research over the years suggests that emotional responses to food/beverage are generally of positive or neutral nature which corresponds to the general purpose of food consumption (Gibson, 2007; Desmet & Schifferstein, 2008; King & Meiselman, 2010). However, some bitter or sour foods could evoke negative emotions such as disgust (Rousmans, Robin, Dittmar, & Vernet-Maury, 2000; Crist et al., 2018). Gutjar et al. (2015) suggest that consumers' emotional experience, in addition to their liking of a food or beverage, can help us better understand food choices behavior.

3.2. Factors influencing emotional responses

Factors influencing emotional responses could be categorized into product-related factors and individual consumer differences. Product-related factors include sensory attributes of the food (e.g., taste and aroma), product characteristics (e.g., temperature and shape) and type of food (e.g., chocolate and juices) (Jiang et al., 2014). Among the sensory factors, taste and smell probably drive majority of the emotional experience in consumers. However, visual cues, including appearance and packaging cues, is also found to be an influential parameter (Desmet & Schifferstein, 2008; Rousset, Deiss, Juillard, Schlich, & Droit-Volet, 2005; Wardy et al., 2017). In a recent study with different types of sweeteners, Wardy et al. (2017) found that in addition to the sweetener quality, emotional responses varied with respect to the packaging of the sweetener as well. Interestingly, Pramudya and Seo (2018) explored the impact of the temperature of emotional responses toward coffee and green tea beverages. Results from this study show that beverages served at warmer temperatures were associated with positive emotions whereas those served at colder temperatures were associated with negative emotions indicating an impact of product characteristics on food/beverage-evoked emotions. Textural aspects of the food, though lesser explored as compared to other sensory attributes, might also have an impact of food/beverage-evoked emotions. For instance, Thompson, Crocker, and Marketo (2010) found that participants in their study associated creamy texture of dark chocolate with emotion terms such as “fun”, “comfortable” and “easy-going”.

As mentioned earlier, in addition to product-related factors, differences in individual consumer traits also influence emotional responses. For instance, different hunger states among participants can lead to differences in emotional responses toward a food or beverage that is not driven by product characteristics. In other words, it is possible that a hungry participant feels emotions such as “satisfied” and “relief” after consuming the food more strongly compared to a sated participant. Moreover, personality traits of the participants can influence their emotional responses, specifically in terms of emotion expressiveness. Desmet & Schifferstein (2008) suggest that sensitive participants are more vulnerable to emotional reactions in response to a food or beverage. In addition, Riggio & Riggio (2002) suggest that personality traits also affect individual emotional expression. Specifically, this study showed that extroverted participants might be more comfortable to express their emotions through self-reported methods as compared to introverted participants whereas participants with higher level of neuroticism might not be able to express their emotions completely based on self-reported measures. Therefore, facial expression analysis might be a better way to measure emotions of participants with higher level of neuroticism. Specifically, in terms of food/beverage-evoked emotions, Samant and Seo (2018) suggest that prediction models of overall liking and preference rank developed using sell-reported emotions, facial expressions and autonomic nervous system responses might vary as a function of different personality traits, especially extraversion and neuroticism. In fact, there is a personality trait known as alexithymia which indicates lack of ability in a person to correctly identify and therefore express emotions (Robino et al., 2016). Another factor influencing individual variation in emotional responses is termed as *granularity* (Barrett, 2004; Kashdan et al., 2015; Prescott, 2017). Granularity refers to “*the degree of fine distinction that individuals make in referring to similar emotional states*” (Prescott, 2017). When a participant rates his/her current emotions using sets of positive and negative descriptors in self-reported measures, different descriptors can be chosen by him/her in highly correlated ways. For example, some participants might not distinguish well between emotion terms such as happiness, joy, enthusiasm, or amusement. These participants can be considered to be low in granularity since the emotions are being identified purely based on valence (please vs. displeasure) (Prescott, 2017). Therefore, individual difference among participants, specifically related to their ability to identify and express emotions in a concurrent manner, probably remains as one of the major challenges among emotion researchers. In addition, other aspect of individual difference with potential to influence emotional responses include demographical data such as culture/ethnicity, gender and age (King & Meiselman, 2010; Jiang et al., 2014; Pramudya & Seo, 2018). Interestingly, King and Meiselman (2010) explored the effect of gender on emotional responses toward savory snacks. Twenty-two emotional terms were reported by females whereas men only reported two emotion terms by women whereas only two emotional items were reported by men. However, there is not enough evidence to support the role of gender in food/beverage-evoked emotions. Pramudya and Seo (2018) in their recent study found that while sensory and emotional responses served as drivers of liking for coffee and tea beverage products among women, only emotional responses were found to be the drivers of liking for men. Due to lack of consensus studies, the role of individual traits on emotional responses remains relatively unexplored area in field of food/beverage-evoked emotions.

3.3. Measurement of emotional responses

3.3.1. Self-reported emotion questionnaires

Inspired from previously developed mood questionnaires, self-reported or standard questionnaires have been developed by researchers to specifically measure food/beverage-evoked emotional responses. For instance, King and Meiselman developed the EsSense Profile® in 2010 by combining words from two previously-established mood questionnaires used in psychology, namely, revised Multiple Adjective Affective Checklist or MACCL-R

(Zuckerman & Lubin, 1985) and Profile of Mood States or POMS (McNair, Lorr, & Droppleman, 1971). Based on rigorous consumer testing, descriptors associated with similar food-evoked emotions were grouped together. The final questionnaire includes 39 emotion terms (25 positive, 3 negative 11 neutral). EsSense Profile® has been gaining importance in the food industry since it has been developed exclusively to measure food/beverage-evoked emotions. In 2016, Nestrud et al. investigated the performance and validity of a reduced version of EsSense Profile®, i.e., EsSense25, comprising of only twenty-five items. It was found that the reduced version performed almost as well as the original version with thirty-nine items. Similarly, a research team from Geneva developed the Geneva Emotion and Odor Scales (GEOS) to measure emotions associated specifically with odors (Chrea et al., 2009). Furthermore, Ferdenzi et al. (2013) developed the UniGEOS, an improvement to GEOS, specifically designed based on information from different countries such as China, Singapore, United States, Switzerland and Brazil, thereby diminishing the cultural barrier to odor-evoked emotional measurement.

Standard emotion questionnaires are perhaps the most popularly used methods for emotional measurement (Lagast, Gellynck, Schouteten, De Herdt, & De Steur, 2017). The most evident advantage of using standard questionnaires is their ease of use and relatively straightforward data handling procedures for statistical analysis. However, there are certain limitations associated with them. Firstly, these questionnaires rely on higher vocabulary level of participants to correctly understand the meaning of emotion terms. This restricts the use of the questionnaire when target participants are kids or adults with lesser developed cognitive ability. To overcome this drawback, visual/non-verbal descriptive terms to measure food-evoked emotions have been introduced. Well-known non-verbal standard questionnaire are Sematic Assessment Manikin or SAM (Bradley & Lang,1994) and Product Emotion Measurement Instrument or PreEmo (Desmet, Hekkert, & Jacobs, 2000). These questionnaires use cartoon or image descriptors as emotion terms instead of words. Dalenburg et al. (2014) conducted a study to compare EsSense Profile® (verbal) and PreEmo (non-verbal) as a tool to measure emotions evoked by breakfast drinks. Results show that both the questionnaires performed equally well to capture emotional responses among participants. In fact, it was found that PreEmo predicted food choices slightly more accurately compared to EsSense Profile®. More recently, Swaney-Stueve, Jepsen, & Deubler (2018) developed the facial emoji questionnaire using different emoticons to measure emotional responses. Although relatively newer, non-verbal emotion questionnaires are gaining momentum due to their flexibility of use among kids and adults.

Another limitation of self-reported questionnaires is their tendency to be generic. In other words, the same questionnaire (e.g., EsSense Profile®) is used for all food products. It is possible that emotions evoked by one food product might not necessarily confirm with emotions evoked by a different product. Therefore, some researchers sought to develop product-specific emotion questionnaire using consumer-defined lexicon. First step to develop a product-specific questionnaire is to generate a list of emotional terms based on participants' feedback. Thereafter, a reduced list is selected and validated against standard questionnaires in terms of reliability in predicting liking, acceptability and preference. For example, Spinelli Masi, Dinnella, Zoboli, and Monteleone (2014) developed *EmoSemio* (23 items) questionnaire for chocolate and hazelnut spreads and compared it with EsSense Profile® (39 items). Results show that the product-specific questionnaire, i.e., *EmoSemio* showed higher potential to differentiate between the chocolate and hazelnut spread samples compared to the standard one, i.e., EsSense Profile® (39 items). However, development of a product-specific emotion question could be a time-consuming process.

By nature, self-reported emotion questionnaires are explicit and require participants to correctly translate their emotional experience into expression. Therefore, these methods are predominantly evaluating conscious or rational emotional processes. However, food-evoked emotions are generally brief and not consciously perceived, which makes the accurate translation from experience to expression difficult. Therefore, there is a need for more implicit methods to measure automatic or non-conscious response to food/beverage-evoked emotions. Commonly studied implicit methods of emotional measurement are facial expression analysis and autonomic nervous system responses, as described below.

3.3.2. Facial expression analysis

Previous research suggests that human express emotions via specific facial changes that are common across cultures, context and gender (Ekman et al., 1987; Tian, Kanade, & Cohn, 2005). Facial expression changes can be voluntary or involuntary. Voluntary changes in facial expressions are mediated by the motor cortex during activities such as talking. On the contrary, changes to facial expressions in response to emotional experience can be considered involuntary and are generally mediated by the amygdala and temporal cortices (Kanwisher, McDermott, & Chun, 1997).

Many software technologies have been developed with inbuilt information to detect facial changes, recognize emotions associated with those changes and quantify them (iMotions, 2017; Tian et al., 2005). Specifically, facial expression analysis consists of three steps: *face acquisition, facial data representation, and facial expression recognition*. In the face acquisition phase, the camera attached to the software locates face region of the participant. Next, facial changes due to emotional experience are monitored. This involves tracking the geometric alignment of the face (nose, eyes, brows, mouth) and their movement. Once facial changes are extracted, software attempts to recognize the emotion quality and intensity of each detected emotions based on existing information (Tian et al., 2005). Facial expressions analysis aims to technologically quantify information that would be otherwise reported by an expert human coder. An expert human coder is trained in identifying an action unit or AU which can be defined as "*discrete, minimally distinguishable action of the facial muscle*". Combination of different action units results in a specific facial expression of emotion.

Facial expression analysis is being increasingly used among researchers to understand acceptability of food or beverage products among consumers (Lagast et al., 2017). Previous research suggests that the relationship between negative emotions and disliked-foods is much stronger compared to positive emotions and liked-foods when evoked-emotions are measured using facial expression analysis (Zeinstra, Koelen, Colindres, Kok, & de Graaf, 2009). In particular, Zeinstra et al. (2009) measured facial expressions in children toward seven beverage samples. Results from this study show that a higher number of total negative action units (AUs) were associated with the disliked samples as compared to positive AUs. However, the distinction between positive and negative facial expressions was unclear for liked samples since total positive AUs were almost equal to negative AUs. Thus, findings from facial expression analysis have to be interpreted carefully as facial movements unrelated to emotional expression can also influence the results.

3.3.3 Physiological measures of autonomic nervous system responses

William James first proposed, in 1884, the possibility of emotions affecting physiological responses, also referred to as "*bodily sensations",* in humans. According to James, these physiological responses were "*almost infinitely numerous and subtle*" (James, 1884). Physiological changes in the human body in response to emotional experiences are mainly associated with the Autonomic Nervous System (ANS). In theory, ANS is responsible for involuntary and reflexive functions of the human body (e.g., heart beat and skin conductance). It is a dual system comprising of sympathetic nervous systems (SNS) and parasympathetic nervous systems (PNS) that work by governing smooth and cardiac muscles throughout the body. SNS is primarily in control of body's "fight or flight" response, meaning that the body is prepared to defend or move away from potentially harmful situations. For instance, if there is an enraging situation, SNS will cause an increase in heart rate and blood sugar while decreasing skin temperature. When this stage subsides, PNS ensures an opposite effect thus balancing energy in the body (Myers, 2005). The most common measures of changes in ANS activity in response to emotional experience are cardiovascular measures (e.g., heart rate, fingertip temperature, systolic and diabolic blood pressure), respiratory measures (e.g., respiration rate, inspiratory and expiratory rate) and electro-dermal measures (e.g., skin conductance level) (Kreibig, 2010). De Wijk et al. (2012) evaluated ANS responses, such as skin conductance, skin temperature and heart rate toward different breakfast drinks. Findings from this study suggest that changes in ANS pattern corresponded with positive and negative emotions for liked and disliked products, respectively.

3.3.3.1 Galvanic skin response

Galvanic Skin Response or GSR is a measure of changes in electrical properties of the skin, particularly those associated with sweat glands mediated by SNS activation (Montagu & Coles, 1966). In other words, emotional responses result in increase in sweat gland activity of the skin. These electrical changes are identified together as Electro-dermal Activity (EDA) (Braithwaite, Watson, Jones, & Rowe, 2013; Vahey & Becerra, 2015). EDA functions via two pathways or processes namely phasic and tonic. Phasic processes are more event-related and are measured over shorter time spans, including quick responses to stimuli. These measures are generally reported in terms of amplitude (magnitude of response) or frequency (number of response). Common GSR measures of phasic EDA are Skin Conductance

Response (SCR) and Skin Resistance Response (SRR), both being reciprocals of each other. On the contrary, tonic process measures slower responses that are spread over a longer time span. Common GSR measures of tonic EDA are Skin Conductance Level (SCL) and Skin Resistance Level (SRL) (Christie, 1981; Vahey & Becerra, 2015).

Emotion-evoked GSR responses are measured by passing AC or DC (mostly DC) current through a circuit that includes a galvanometer, electric battery and human body contact. Specifically, electrodes (Ag/AgCl) are placed on the forefinger and middle finger of a panelist's non-dominant hand (Rousmans et al., 2000). In theory, the resistance between these two electrodes is virtually the sum of skin resistance, assuming interior body resistance to be negligible. Increase in skin conductance (thereby decrease in resistance) is interpreted as emotional arousal due to SNS activation (Braithwaite et al., 2013).

3.3.3.2 Cardiovascular response

Cardiovascular measures, particularly heart rate (HR; beats/minute) and heart rate variability (HRV; time interval between two beats) have been used extensively in response to food/beverage-evoked emotions. Common method to measure heart rate response is by placing three silver electrodes in precordial position of the panelist (one of musculature of right side of neck and other two on left lateral abdomen). Another method is by placing the sensor on panelists' earlobe or finger (de Wijk et al., 2012, 2014). HR is recorded in terms of consecutive peaks of electrocardiogram R waves representing electrical stimulus of heart's conducting system (Leterme et al., 2008; Rousmans et al., 2000). Interestingly, heart rate measures have been found to be sensitive to valence dimension of emotion, that is, they can discriminate between pleasant and unpleasant stimuli (Danner, Haindl, Joechl, & Duerrschmid, 2014).

Another cardiovascular response commonly used a measure of emotional response is skin temperature. Some studies show that SNS activation can cause thermoregulatory changes in the body thereby affecting skin surface temperature (Kistler, Mariauzouls, & von Berlepsch, 1998). Specifically, nerves present on the skin surface causes changes in skin blood flow and acral skin temperature due to SNS activation. It is suggested that in relaxed state, a person’s vessels are dilated (vasodilation) causing the skin temperature to be warmer. On the other hand, in tensed state, vessels are constricted (vasoconstriction) and skin temperature is cooler (Kistler et al. 1998). Interestingly, previous research suggests that negative emotions tend to cause vasoconstriction resulting in decrease in skin temperature, whereas positive emotions cause vasodilation thereby increasing skin temperature (Kreibig, 2010).

4. Association between consumer behavior, sensory perception, and emotional responses

So far, we have addressed the characteristics and measurement of consumer behavior with respect to acceptance, including liking and purchase intent, as well as preference among consumers. In addition, sensory attribute perception and emotional responses driving consumer behavior have been highlighted. Researchers have tried to explore the association between consumer behavior, sensory perception and emotional responses. Some researchers demonstrate the relationship between emotions and liking (Leterme et al., 2008; Rousmans et al., 2000) whereas some believe that food-evoked emotions provide better discrimination between samples as compared to liking ratings (Gutjar et al., 2015; Ng et al., 2013). However, this association heavily depends on the methods applied to measure evoked emotions. Table 1 provides information about a few recent and relevant research studies conducted to improve understanding of consumer behavior with respect to liking, preferences or purchase intent based on sensory attribute intensities and emotional responses. Measures of emotional responses included here are explicit measures, i.e., self-reported emotion questionnaires, and implicit measures, i.e., facial expression analysis and autonomic nervous system responses.

As mentioned earlier, self-reported emotions show moderate to strong correlation with liking, with positive emotions associated with higher liking and negative emotions associated with lower liking (Cardello et al., 2012; Dalenburg et al., 2014; Samant et al., 2017). Changes in self-reported emotions as a function of sensory attribute intensities have not been studied exclusively since the association might be mediated by acceptability of the attribute intensity. For example, He, Boesveldt, de Graaf, and de Wijk (2016) measured emotional responses to orange (pleasant) and fish (unpleasant) odors at three different concentrations using self-reported measures such as PrEmo and facial expressions, in addition to odor intensities and liking. Though both measures differentiated pleasant and unpleasant emotions with respect to valence of the odor, facial expressions also varied with odor intensity. In particular, intensity of "scared" emotion was stronger at higher concentrations of the odors. In a similar study with breakfast drinks, de Wijk et al. (2014) evaluated the facial expressions and ANS parameters evoked by breakfast drinks, in addition to liking and intensity ratings. Results from this study show that increased heart rate and skin temperature were associated with higher liking of the samples as well as lower overall intensities. It was also suggested that increased intensities were associated with more negative emotions measured using facial expressions. These results are similar to those found in He et al. (2016) suggesting that the association between sensory attribute intensities and emotional responses could be mediated by acceptability ratings. Interestingly, some studies show that emotions measured using implicit methods are more sensitive to negative acceptability behavior as compared to positive behavior (Danner, Sidorkina et al., 2014;

Zeinstra et al., 2009). For instance, Danner et al. (2014) measured emotional responses in terms of facial expressions and ANS responses along with liking ratings toward orange juice samples. It was found that the disliked samples caused more intense ANS and facial expressions response compared to samples that were liked. Similarly, Zeinstra et al. (2009) evaluated preference and emotional responses using facial expressions in response to seven liquids including apple juice, skimmed milk, sauerkraut juice, asparagus solution, beetroot juice, a bitter solution, and a sweet solution. Interestingly, a two-stage preference order approach was used. Firstly, the child was provided with the seven liquids and asked to place liquid on a smiley descriptor category (like, neutral or dislike) indicating his/her preference. Next, the child tasted samples within each category and indicated the sample they liked best. This process was repeated for each sample in a category and all categories until a rank order for all seven samples was reached. Results suggest that the lesser-liked beverages showed more recognizable negative emotions compared to neutral or positive emotions toward liked-samples.

It is worth noting that generalizing emotional responses toward food/beverages, especially those measured using implicit measures such as ANS and facial expressions, is a challenge. Firstly, some researches measure emotions in terms of dimensions, i.e., arousal or valence whereas some researchers believe in the discrete emotion theory and measure individual emotions such as “fear” or “joy” (Mauss & Robinson, 2009). There is no common notion of which theory of emotions stands corrected and therefore interpretation of results is dependent on whether emotions are measured as discrete entities or common dimensions. Second, individual differences among participants (explained in section 3.2) is one of the primary reasons for this challenge. For instance, de Wijk et al. (2012) studied emotional responses to a variety of foods for young adults and children. ANS measures of emotional response were skin conductance resistance, heart rate, finger temperature and facial expressions. ANS responses were measured continuously to give information about changes in emotional responses during first sight, smelling and tasting the sample. In addition, overall liking of the food was also measured. Results suggest that first sight of the “disliked” food increased skin conductance resistance compared to “liked” foods. However, finger temperature and heart rate were not affected. It was also found that heart rate of young adults decreased during smelling but increased while tasting the food sample. Moreover, this study reports an increase in finger temperature due to liked foods compared to disliked foods contradicting the findings of Danner et al. (2014) on beverages which reported stronger ANS response to disliked foods. Interestingly, differences in study designs also lead to varying emotional responses toward food or beverages. In particular, previous research suggests emotional responses toward a product can vary under blind tasting conditions vs. informed conditions, especially those emotions associated with purchase behavior (Gutjar et al., 2015; Kytö et al., 2018; Songa et al., 2018). Here, blind condition is when participants taste the sample without any product information whereas informed condition is when relevant product label information is provided to the participants.

Based on the review above, we can say that holistically understanding the association between emotional responses and consumer behavior requires optimization of the method(s) used to measure emotional responses. Currently there is no gold standard since both explicit and implicit measures have their share of advantages and disadvantages. However, it is possible to consolidate the advantages of both implicit and explicit methods to provide better understanding of consumer acceptability and preference toward beverage sample.

Table 1: Measurement of sensory perception, and emotional responses to understand consumer behavior

Food/beverage	Acceptability/preference/ purchase intent	Emotional responses measure	Sensory attribute intensity	Reference
Beer	Acceptability	FE, ANS	Foam, color, aroma, mouthfeel, taste, flavor	Viejo et al. (in press)
Bitter taste solutions	Acceptability	FE	Taste	Crist et al. (2018)
Assorted foods	Acceptability	SE	Appearance, flavor, taste, texture, after taste, mouthfeel	Jaeger et al. (2018)
Quark	Acceptability, purchase intent	SE	-	Kytö et al (2018)
Fruit juices	Acceptability	FE	-	Zhi et al., (2018)
Flavored chips	Acceptability	SE, FE	-	Le Goff & Delarue (2017)
Australian white wine	Acceptability, purchase intent	SE	aroma, flavor, mouthfeel	Danner et al. (2017)
Beer	Acceptability	SE, FE, ANS	aroma	Beyts et al. (2017)
Orange and fish	Acceptability	SE, FE	odor/aroma	He et al. (2016)
Milk	Acceptability	SE, FE	-	Walsh et al. (2015)
Breakfast drinks	Acceptability	SE	-	Gutjar et al. (2015)
Hazelnut and cocoa spread	Acceptability	SE	-	Spinelli et al (2015)
Assorted beverages	Acceptability	FE, ANS	-	Danner, Haindl et al. (2014)
Orange juice	Acceptability	FE	-	Danner, Sidorkina et al. (2014)
Breakfast drinks	Acceptability	FE, ANS	overall	De Wijk et al. (2014)
Blackcurrant squash	Acceptability	SE	-	Ng et al. (2013)
Assorted foods	Acceptability	ANS	-	De Wijk et al (2012)
Assorted food and food names	Acceptability	SE	-	Cardello et al. (2012)
Assorted beverages	Preference	FE	-	Zeinstra et al. (2009)
Assorted beverages	Acceptability	ANS	Sweet taste	Leterme et al. (2008)
Sweet, sour, salty, bitter taste solutions	Acceptability	ANS		Rousmans et al (2000)

SE, FE and ANS stand for self-reported emotion questionnaires, facial expression analysis and autonomic nervous system responses, respectively.

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CHAPTER 3

Predicting consumer liking and preference based on emotional responses and sensory perception: A study with basic taste solutions

Abstract

Traditional methods of sensory testing focus on capturing information about multisensory perceptions, but do not necessarily measure emotions elicited by these food and beverages. The objective of this study was to develop an optimum model of predicting overall liking (rating) and preference (choice) based on taste intensity and evoked emotions. One hundred and two participants (51 females) were asked to taste water, sucrose, citric acid, salt, and caffeine solutions. Their emotional responses toward each sample were measured by a combination of a self-reported emotion questionnaire (EsSense25), facial expressions, and autonomic nervous system (ANS) responses**.** In addition, their perceived intensity and overall liking were measured. After a break, participants re-tasted the samples and ranked them according to their preference. The results showed that emotional responses measured using self-reported emotion questionnaire and facial expression analysis along with perceived taste intensity performed best to predict overall liking as well as preference, while ANS measures showed limited contribution. Contrary to some previous research, this study demonstrated that not only negative emotions, but also positive ones could help predict consumer liking and preference. In addition, since there were subtle differences in the prediction models of overall liking and preference, both aspects should be taken into account to understand consumer behavior. In conclusion, combination of evoked emotions along with sensory perception could help better understand consumer acceptance as well as preference toward basic taste solutions.

Keywords: Consumer behavior; Emotion; Sensory perception; Taste; Acceptance; Preference

1. Introduction

Any new food product is typically subjected to consumer affective tests before its market introduction. These affective tests primarily include acceptance rating tests as well as preference ranking ones (Meilgaard, Civille, & Carr, 2015). Researchers often integrate sensory perception cues, such as perceived intensities of taste and flavor, with acceptance tests to better understand product quality and liking. While intensities of taste and flavor are subject to consumer liking, a direct relationship between intensity and liking is not evident since it varies with individual sensory attributes as well as type of food product being tested. Stolzenbach, Bredie, Christensen, and Byrne (2016) investigated the relationship between likings toward different apple juices and corresponding apple flavor intensities. It was found that a strong positive correlation existed between apple flavor intensity and overall liking for sweet-tasting apple juices but not for sour-tasting ones. These results indicate that consumers' perceived intensity of sensory attributes might not be clear indicator of consumer acceptance and preference. It is worth noting that consumer behaviors are associated with not only complex cognitive processing of multisensory perceptions, but also emotional experiences with what they eat or drink (Hirschman & Holbrook, 1982; Berridge, 1996).

Traditional methods of sensory testing have been developed to understand consumers' multisensory perceptions such as sensory attribute intensities, but not emotion elicited by food or beverages. However, researchers have recently gained interest in studying food/beverage-evoked emotions to better understand consumer behavior. It brings us to the question, "*What is a food/beverage-evoked emotion?*" Food/beverage-evoked emotions could be defined as "a brief but intense physiological and/or mental reaction to a food or beverage item" (Bagozzi, Gopinath, & Nyer, 1999; King & Meiselman, 2010; Kenney & Adhikari, 2016). Food/beverage-evoked emotions are generally positive or neutral (neither positive nor negative) in nature, which is coherent with the general purpose of consuming food or beverages (Gibson, 2007; King & Meiselman, 2010). Many studies have attempted to find the association of food/beverage liking or acceptance with evoked emotions (for a review, Jiang, King, & Prinyawiwatkul, 2014; Kenney & Adhikari, 2016). Specifically, Ng, Chaya, and Hort (2013) studied emotional responses toward eleven blackcurrant squashes. Positive emotions such as “happy”, “pleasant”, and “joyful” were found to have strong positive correlations with overall liking of the beverage. Even neutral emotions such as “polite” and “understanding” were found to have positive correlations with better-liked beverages. However, lesser-liked beverages evoked more negative emotions such as “disgusted”, “annoyed”, and “angry”.

One of the major challenges encountered by researchers studying emotional responses is how to accurately measure food/beverage-evoked emotions. A common approach for this purpose is the use of self-reported ratings of emotion terms on questionnaires such as EsSense Profile® (King & Meiselman, 2010) or its reduced version known as EsSense25 (Nestrud, Meiselman, King, Lesher, & Cardello, 2016). Another approach to measure food/beverage-evoked emotions is facial expression (FE) analysis. This is typically carried out using computer software with inbuilt information about changes in human facial expression to different emotions (Tian, Kanade, & Cohn, 2005). A third method of measuring emotional responses is based on the theory that emotional experiences are manifested into physiological changes in the human body, particularly those regulated by autonomic nervous system (ANS) (Kreibig, 2010). These changes are mainly observed in electro-dermal activity (EDA) of the skin measured as skin conductance response (SCR), cardiovascular activity measured as heart rate (HR), and skin temperature (ST) (Kenney & Adhikari, 2016). The methods listed above could be used individually or in combination to measure food/beverage-evoked emotions.

There is a knowledge gap with respect to the association between food/beverage-evoked emotions and consumer behavior. Firstly, even though several studies have attempted to use a combination of facial expression and ANS responses to predict consumer behavior (de Wijk, Kooijman, Verhoeven, Holthuysen, & de Graaf, 2012; de Wijk, He, Mensink, Verhoeven, & de Graaf, 2014), limited research has been done using facial expression analysis and ANS response in combination with self-reported emotions to measure food/beverage-evoked emotions. In addition, it still remains unclear how much each method contributes to a prediction of consumer behavior regarding food/beverage liking and preference. Secondly, as mentioned earlier, even though there have been some studies investigating the association between consumer liking (rating data) and emotional responses, not many studies have tried to investigate the association of food/beverage evoked emotions with preferences (ordinal data). Although both acceptance and preference tests are designed for a common goal of understanding consumer behavior, results obtained from both have shown discrepancies in the past (Lévy & Köster, 1999). In a study with alcoholic beverages, Lévy and Köster (1999) asked participants to taste a glass of the beverages (10 mL) and rate their hedonic response toward each on a line scale. Later, participants re-tasted the sample and chose the most preferred sample (rank). It was found that the hedonic response did not correspond with preference data for more than 30% of the participants, indicating that it is essential to consider both acceptance and preference data when establishing an association with emotional responses. There have been studies recently that aimed to develop a predictive model to understand food choice or preference among consumers based on emotional responses (Gutjar, Dalenberg, de Graaf, de Wijk, Palascha, Renken, & Jager, 2015a). However, they were restricted to use of self-reported techniques to measure emotional responses and did not account for facial expression or ANS responses in their predictive model. Thirdly, there is limited information on how sensory perceptions and emotional responses together help to predict consumer acceptance and preference.

In an attempt to address the above limitations, the objective of this study was to develop a novel methodology to predict consumer acceptance (liking) and preference (choice) of basic taste solutions using taste intensity perceptions and emotional responses measured by a combination of self-reported emotions, facial expressions, and ANS responses. The reasons to choose basic taste solutions as a test sample in this study were (1) to avoid unwanted movement of facial nerves that are generally encountered during chewing of a solid food, and (2) to reduce bias from multi-sensory perception of different sensory attributes such as aroma and texture (Bult, de Wijk, & Hummel, 2007; Seo & Hummel, 2012). This is the first study, to the best of the authors' knowledge, to develop a prediction model of consumer acceptance as well as preference using emotional responses and sensory attribute perceptions as independent variables.

2. Materials and Methods

The protocol used in this study was approved by the Institutional Review Board of the University of Arkansas (Fayetteville, AR). Prior to participation, experimental procedure was explained and a written consent indicating voluntary participation was obtained from each participant.

2.1 Participants

Using an online survey program (http://www.surveymonkey.com), a survey containing the 10-item Perceived Stress Scale (PSS), designed to measure the degree to which situations in everyday life are perceived as stressful (Cohen, Kamarch, & Mermelstein, 1983), were sent out volunteers registered through a consumer profile database from the

University of Arkansas Sensory Service Center (Fayetteville, AR, U.S.A.) that comprises of more than 6,200 Northwest Arkansas residents. Participants with high chronic stress, scored higher than 25-point on the PSS were excluded from the study to minimize potential influences of mental stress on perceived intensity and acceptability of tasting substances (Al'absi, Nakajima, Hooker, Wittmers, & Cragin, 2012; Samant, Wilkes, Odek, & Seo, 2016). In addition, volunteers who had known food allergies or a clinical history of major diseases were not included in the study. One hundred and two healthy adults (51 men and 51 women; mean age ± standard deviation = 39 ± 14 years) participated in this study.

2.2 Sample preparation

Sweet, sour, salty, and bitter-tasting solutions were prepared with pure cane sugar (Great Value™, Wal-Mart Stores, Inc., Bentonville, AR), citric acid (Sigma-Aldrich Fine Chemicals or SAFC®, St Louis, MO), salt (Morton Salt, Inc., Chicago, IL), and caffeine (Aldrich Chemical Company, Inc., Milwaukee, WI), respectively. Each taste solution was prepared at two concentration levels, i.e., "low" and "high", which correspond to the numerical rating "5" and "10", respectively, on the 0- to 15-point intensity scale (Meilgaard et al., 2015). Converting these numerical ratings to concentrations, the "low" and "high" levels for each taste solution, respectively, were as follows (Meilgaard et al., 2015): sweet (5% and 10% w/v), sour (0.10% and 0.15% w/v), salty (0.35% and 0.55% w/v), and bitter (0.08% and 0.15% w/v). In addition, spring water (Mountain Valley Springs Co., LLC Hot springs, AR) was included as a control. All samples were served at room temperature (approximately, 23 °C) in 60-mL soufflés cups (Pettus Office Products, Little Rock, AR).

2.3 Measurement of emotional responses

2.3.1 Approach 1: Self-reported emotions (EsSense 25)

EsSense25 (25 items) (Nestrud et al., 2016), a reduced version of the EsSense Profile® (39 items) (King & Meiselman, 2010), was used in this study to evaluate participants' self-reported emotions on a 5-point scale ranging from 1 (not at all) to 5 (extremely). Overall performance of both questionnaires was found to be similar with respect to food-name evaluations, brand evaluations, and product testing methods (Nestrud et al., 2016).

2.3.2 Approach 2: Facial expression (FE) analysis

Facial expressions were recorded and analyzed using iMotions software (version 6.1, iMotions, Inc., MA) that tracks and analyzes frame-by-frame presences (sampling rate of 102.4 Hz) of seven basic universal expressions of human emotions (joy, anger, surprise, fear, contempt, disgust, and sadness). Each of these seven basic emotions was assigned a numerical value called "evidence value" (EV) representing the odds, in logarithmic (base 10) scale, of the target expression being present when compared to each participant's neutral state (iMotions, 2017). A positive (negative) EV of q for "joy" emotion indicates that an expert human coder is 10^q times more (less) likely to categorize that expression as joyful as compared to the participants' neutral state. For example, an EV of "+2" ("-2") for joyful emotion represents that the facial expression is 100 times more (less) likely to be categorized as joyful compared to the neutral state. An EV of "0" for joyful emotion indicates an equal chance that the facial expression is to be categorized as joyful as in the neutral state (iMotions, 2017). It should be noted that an expert human coder is trained in identifying an action unit or AU, defined as *"discrete, minimally distinguishable action of the facial muscle"* (Oster, 1978), and associating it with a particular emotion.

2.3.3 Approach 3: Physiological autonomic nervous system (ANS) measures

Emotional responses can affect sweat gland activity identified together as electro-dermal activity (EDA) of the skin. EDA functions via two pathways/processes, namely phasic and tonic. Phasic processes are more event-related and are measured over shorter time spans, including quick responses to stimuli (few seconds after onset of stimuli). On the contrary, tonic process measures slower responses that are spread over a longer time span (few minutes after onset of stimuli). Since emotions are categorized as quick response to stimuli, we used phasic EDA measured in terms of skin conductance response (SCR). In addition to EDA, since cardiovascular activity in the body is also affected due to emotions, heart rate (HR) and skin temperature (ST), which are commonly used to indicate changes in cardiovascular activity (Kreibig, 2010), were measured in this study.

In this study, SCR (unit: μSiemens) and HR (unit: beats/minute) were measured using SHIMMER™ sensor (SHIMMER™, Dublin, Ireland). SHIMMER™ is a flexible sensing platform used for non-invasive biomedical research purposes (Burns et al., 2010). To measure SCR, two Velcro-strap electrodes were placed on proximal phalanges of index and middle fingers, on the non-dominant hand of the participant. HR was measured by placing an electrode on proximal phalanges of the participants' ring finger. Data was collected at a sampling rate of 102.4 Hz. In addition, ST (unit: °C) was measured using eSense Skin Temperature Sensor (Mindfield® Biosystems Ltd., Gronau, Germany) for Android devices. The sensor was placed on the palm of non-dominant hand and measured ST every 0.2 s.

2.4 Measurement of taste intensity and overall liking

Participants were asked to rate the perceived taste intensity of each sample on a 15-cm line scale ranging from 0 (extremely weak) to 15 (extremely strong). In addition, participants rated their overall liking of the sample on a 9-point hedonic scale ranging from 1 (dislike extremely) to 9 (like extremely).

2.5 Procedure

The study was conducted over a span of two days (i.e., test sessions), one week apart. Each participant attended both a "low" and a "high" concentration test sessions. Half of the participants tasted the "low" concentration samples on Day-1, while the other half experienced it on Day-2, and vice versa with respect to "high" concentration samples.

2.5.1 Instruction and experimental set-up

Figure 1 provides an overall scheme of experimental procedure. On arrival, each participant was asked to sit comfortably and the experimental procedure was explained. The participant was asked to rate 25 emotions on EsSense25 based on how much of each emotion she/he felt at that moment (as described in section 2.3.1). A camera (Logitech Europe S.A., Nijmegen, Netherlands) was placed in front of the participant to measure facial expression. To get a clear view of the participant's face, heights of the camera and chair were adjusted. Non-dominant hand of the participant was cleaned with 70% (v/v) isopropanol (PL developments, Clinton, SC) to improve skin conductance. In addition, a conductive electrode cream (Synapse®, Kustomer Kinetics, Inc., Arcadia, CA) was gently smeared over proximal phalanges of index and middle finger on the non-dominant hand of the participant. Electrodes to measure SCR, HR, and ST were attached to the non-dominant hand of the participant (as described in section 2.3.3).

2.5.2 Test session

During each test session, each participant was asked to taste a total of five samples, which included sweet, sour, salty, bitter-tasting solutions and spring water as a control. The presentation order of the samples was randomized across both days, ensuring a control was presented on both days. Approximately 45-mL of each sample was presented in a 60-mL soufflés cup identified with a three-digit code. The participant was instructed to pour the entire sample in their mouth and swallow while looking at the camera. FE and ANS responses were measured 15 s before participants poured the sample in her/his mouth ("pre-consumption" time window) and 15 s after she/he swallowed the sample ("post-consumption" time window). Following that, the participant was asked to rate each emotion on EsSense25 again, to measure how the sample made her/him feel. In addition, the participant rated her/his perceived intensity and overall liking of the sample. A 2-min break was given between samples. It should be noted that the participant was instructed to keep her/his hand movement to the minimum and advised against talking during entire length of the study to avoid noise in the FE and ANS response measures.

Once a participant tasted all five samples during a test session, she/he had a break for about 10 min. Next, the participant was asked to re-taste the five samples again in a different room. However, the samples were presented with different three-digit codes to minimize potential recollection or learning-related influences. After tasting all five samples, participants ranked them in order of preference (1: most preferred; 5: least preferred).

2.6. Data analysis

2.6.1. Self-reported emotions (EsSense25)

In order to obtain data on emotions evoked by samples, each participant's baseline rating of each emotion term, i.e., rating prior to beginning of the study, was subtracted from rating after consumption of each sample. The subtracted values were used for further statistical analysis.

2.6.2. Facial expression analysis and ANS responses

FE, SCR, HR, and ST were extracted 15 s before and after consumption of each sample. Prior to statistical analysis, we investigated how FE and ANS responses could change before and after consumption. As shown in Figure 2, in the pre-consumption time window, disgust emotion showed a fairly stable response during first 5 s, but the value gradually increased beyond that, reaching a maximum during the last 3 s. HR also showed a similar trend (Fig. 3). Such variations in participants' FE and ANS responses just before consumption have been observed in previous studies (He, Boesveldt, Delplanque, de Graaf, & de Wijk, 2017). To avoid biased contribution of the anticipatory phase, we decided to consider the first 5 s of pre-consumption time window (referred as "Pre Consumption") for FE as well as ANS responses for each sample (Fig. 2 and 3).

In the 15 s of post-consumption time window, while disgust emotion of FE showed maximum variation during first 5 s (Fig. 2), HR showed maximum change over first 10 s (Fig. 3). It has been reported that changes in ANS response have a slower onset compared to facial expressions (Danner, Sidorkina, Joechl, & Duerrschmid, 2014). Therefore, we decided to use first 5 s of FE and first 10 s of ANS responses from the post-consumption time window (referred as "Post Consumption") for each sample (Fig. 2 and 3).

Finally, data of facial expressions and ANS responses obtained during "Pre Consumption" stage was subtracted from those obtained during "Post Consumption" stage of each sample, for all participants. These values were used for further statistical analysis.

2.6.3. Statistical analysis

Data was analyzed using JMP® Pro (version 13.0, SAS Institute Inc., Cary, NS). Step-wise multiple linear regression analysis and ordinal logistic regression analysis were conducted to predict overall liking and preference rank, respectively. Specifically, while overall liking and rank were chosen as the dependent variables (fitted separately), all other variables (taste intensity, self-reported emotions on EsSense25, EVs of seven basic emotions, SCR, HR, and ST) were used as independent variables. A stepwise regression is a sequential process to fit statistical models. At each step of fitting model, an explanatory variable can be either added or deleted from the next fit model (Jobson, 1991). In addition, in ordinal logistic regression, cumulative probability of being at or below each response level is modeled by a curve. Since the main focus of this study was to determine the predictive values of the independent variables as well as to find an optimum model, we constructed a total of 14 statistical models for each dependent variable, i.e., overall liking or preference rank. These models contained different combinations of independent variables and were compared in terms of model performance. *P*-value stopping criterion was chosen for optimum variable selection; probability for a predictor to enter and leave the model was set at 0.25 and 0.05, respectively. Parameter estimates (β) for each predictor in the model, along with their corresponding standard error and level of significance were reported. It should be noted that interpretation of β is different for multiple linear regression and ordinal logistic regression. By definition, in the former, β values represents *an estimate of change in dependent variable that, in turn, correspond to a unit increase in that independent variable while all other independent variables are held constant* (Klimberg & McCullough, 2013). For instance, a negative value of β indicates that increasing the predictor value will decrease the dependent variable value, provided all other independent variables are constant. However, negative value of β in ordinal logistic regression represents increase in probability in the higher numbered response categories (i.e., “less preferred” in this study). Multicollinearity among predictors was ensured by examining variable inflation factor (VIF) values for each predictor. Multicollinearity occurs when predictors provide redundant information due to high correlation with each other. A general rule of thumb is that VIF > 5 are to be used in the model with caution, whereas VIF > 10 represents serious multicollinearity (Klimberg & McCullough, 2013). Predictors in all the models constructed in this study had VIF < 3, indicating low multicollinearity.

Models constructed for overall liking using multiple linear regression approach were compared using adjusted R^2 (R^2_{adj}), root mean square error (RMSE), Mallows' C_p, total number of predictors in the model (p), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC). These parameters have been extensively used in the past for multiple linear regression model comparison (Montgomery, Peck, & Vining, 2015). R^2_{adj} assesses overall adequacy of the model while penalizing the model if the added predictors are not helpful (Montgomery et al., 2015). RMSE gives an estimate of the degree of variation in the model prediction. Mallows' C_p statistic is used to assess a model for least square regression models to by comparing with p. A model is considered good fit if C_p approaches p. AICc is the small-sample-size corrected version of the AIC used to measure goodness of fit for a model. BIC is another criterion for model section among a finite set of models. In general, lower values of C_p, AICc, and BIC are preferred (Montgomery et al., 2015). Models constructed for preference rank using multiple ordinal logistic regression approach were compared using R^2, log likelihood, AICc, and BIC. Log-likelihood estimates are often used as model comparison measures for ordinal data with higher values being considered as better fit. However, rather than maximizing the likelihood function, using negative value of the natural logarithm of the likelihood function is found to be more convenient. In other words, the aim is to minimize *–Log-likelihood* (JMP®, 2013). Furthermore, Pearson's and Spearman's correlation analyses were performed to determine the relationships between actual and predicted values of overall liking and preference rank, respectively. Statistical significance was set at 5% level of significance ($P < 0.05$).

3. Results

3.1. Relationships of taste intensity with overall liking and preference rank

As shown in Tables 1 and 2, higher taste intensities were associated with lower overall liking as well as lower preference (1: most preferred; 5: least preferred) among participants.

3.2. Relationships of emotional responses with overall liking and preference rank

3.2.1. Self-reported emotions (EsSense25)

As shown in Table 1, positive self-reported emotions such as “active”, “good”, “nostalgic”, and “satisfied” show positive relationships with overall liking. Negative emotions such as “disgusted” were negatively associated with overall liking. Similarly, for preference rank, higher “disgusted” and lower “satisfied” emotions resulted in participants showing lesser preference for the sample. Interestingly, even though higher “calm” emotion was expected to be associated with higher overall liking and preference rank, the opposite trend was observed for both in this study (Tables 1 and 2).

3.2.2. Facial expressions

In terms of FE predictors, higher EVs of “surprise” and “joy” emotions but lower EVs of negative emotions such as “disgust”, “fear”, and “sadness” resulted in higher overall liking among participants (Table 1). When predicting preference rank (Table 2), lower EVs of negative emotions such as “disgust” and fear” were associated with higher preference. In addition, higher EVs of “surprise” and “joy” emotion were associated with higher preference.

3.2.3. Physiological autonomic nervous system responses

Stepwise regression did not find any of the ANS responses as significant predictors of overall liking as well as preference rank. (*Note: Since models constructed with only ANS* *responses predicting overall liking as well as preference rank did not yield any significant predictors, they have been excluded from Tables 1 to 4*).

3.3. Optimum model selection

Model performance parameters for each model constructed for overall liking and preference rank are given in Tables 3 and 4, respectively. As shown in Table 3, a multiple linear regression model "J" to predict overall liking, using a combination of taste intensity, self-reported emotions, and facial expressions, were found to be the optimum model since it produced the highest R^2_{adj} (0.5), the lowest RMSE (1.62), and lower values in AICc (3,892.88) and BIC (3,956.58). C_p for this model was around 18. As shown in Table 1, significant predictors for this model were taste intensity (β = -0.1, $P < 0.001$), self-reported emotions such as "active" (β = 0.16, $P < 0.01$), "calm" (β = -0.20, $P < 0.001$), "disgusted" (β = -0.77, $P < 0.001$), "good" (β = 0.22, $P < 0.01$), "satisfied" (β = 0.45, $P < 0.001$), and "secure" (β = -0.21, $P < 0.001$), along with facial expressions measured in terms of EVs of "joy" (β = 0.08, $P < 0.05$), "fear" (β = -0.27, $P < 0.001$), "contempt" (β = 0.28, $P < 0.01$), and "disgust" (β = -0.31, $P < 0.001$).

Similarly, the multiple ordinal logistic regression model "J" to predict preference rank, using a combination of taste intensity, self-reported emotions, and facial expressions, was found to be optimum since it yielded the highest R^2 (0.10) and -log-likelihood (1,472.72) values, as well as the lowest AIC (2,969.75) and BIC (3,028.57) values (Table 4). As shown in Table 2, significant predictors for this model were taste intensity (β = -0.08, $P < 0.001$), self-reported emotions such as "calm" (β = -0.16, $P < 0.01$), "disgusted" (β = -0.60, $P < 0.001$), "good" (β = 0.16, $P < 0.05$), and "satisfied" (β = 0.23, $P < 0.001$), along with facial expressions measured in terms of EVs of "joy" (β = 0.10, $P < 0.01$), "anger" (β = 0.24, $P < 0.01$), and "disgust" (β = -0.28, $P < 0.001$).

3.4. Relationship between observed and predicted values with respect to overall liking or preference rank in the optimum model generated in this study

The optimum model "J" developed for predicting overall liking in this study showed a strong positive correlation between observed values and predicted values of overall liking ($r = 0.71$, $P < 0.001$). Similarly, the optimum model "J" predicting for overall preference showed a moderate to strong correlation between observed and predicted values ($rho = 0.53$, $P < 0.001$).

4. Discussion and Conclusion

This study developed optimum prediction models for overall liking rating and preference rank toward basic taste solutions using a combination of sensory attribute intensity and emotional responses measured by both emotion questionnaire (EsSense25) and facial expression analysis.

Taste intensity was found to have a negative association with overall liking as well as preference, i.e., higher taste intensities were liked less and had lower preference among participants. As mentioned earlier, there is no universal association of sensory attribute intensity with liking or preference. The relationship changes dynamically with the attributes in questions. In an experiment investigating the relationship between basic taste intensity and liking, Pangborn (1970) reported that 65% of total participants (15 out of 23) showed decreasing trend in liking when concentration of salt solution was increased from 0.0% to 0.9% (w/v) in specific increments; around 9% of total participants showed a positive trend, and remaining 26% of total participants showed a U-shaped trend with maximum liking at around 0.3% (w/v). Based on previous and present findings, it seems that taste intensities only measure a part of consumer acceptance and behavior.

The present study found significant relationships of emotional responses with overall liking and preference. In particular, self-reported emotions measured by emotion questionnaire (EsSense25) and facial expression analysis showed stronger relationships with the consumer behavioral aspects than did ANS responses. As measured by Essense25, participants felt more positive emotions such as “active”, “good”, “nostalgic”, and “satisfied” after drinking samples they liked and also preferred. In addition, higher negative emotions such as “disgusted” were reported for lesser-liked and lower-preference samples. These results are consistent with previous findings obtained by the self-reported emotions (Ng et al., 2013; Gutjar, de Graaf, Kooijman, de Wijk, Nys, ter Horst, & Jager, 2015b; Borgogno, Cardello, Favotto, & Piasentier, 2017). Specifically, Borgogno et al. (2017) in a recent study explored emotional responses measured by EsSense25 toward beef samples. They found that higher liking of beef was associated with positive emotions (e.g., “active”, “satisfied”), while negative emotions (e.g., “disgusted”, “guilty”) were connected to lower liking.

It is important to understand that self-reported emotions provide discrete information about emotional responses toward the samples, whereas facial expressions provide a continuous measurement. Previous research suggests that emotions measured with facial expressions show a stronger relationship between negative emotions and disliked-foods than for positive emotions and liked-foods (Zeinstra, Koelen, Colindres, Kok, & de Graaf, 2009). More specifically, Zeinstra et al. (2009) compared facial expressions in children toward seven beverages. In their study, negative facial expressions for disliked samples (e.g., bitter tasting solution) was easily recognized due to high number of total negative action units (AUs) associated with the samples as compared to positive AUs. However, the distinction between positive and negative facial expressions was less clear for liked samples (e.g., apple juice) since total positive AUs were almost equal to negative AUs. In the present study, participants expressed more “disgust”, “fear”, and “sadness” when they disliked the samples and/or preferred them less. However, positive expressions such as “joy” and neutral expressions such as “surprise” were found to be associated with higher liking and preference among participants (Tables 1 and 2). Therefore, based on current results, not only the negative emotion expressions, but also positive and neutral expressions can help understand consumer acceptance and preference.

Physiological manifestation of emotional responses, measured in terms of ANS responses, did not show any significant relationship with overall liking and preference. Although these relationships have been reported in the previous studies (de Wijk et al., 2012, 2014), there is no consistent association between ANS responses patterns and emotional responses (also see Kreibig, 2010). In a previous study, Leterme, Brun, Dittmar and Robin (2008) investigated the relationship between ANS measures (skin resistance, heart rate, and skin temperature) and hedonic ratings of four beverage samples: sweet solution, orange juice, coke, and lemonade. No significant correlations were found between hedonic ratings and any of the ANS measures. This lack of correlation was observed in all four samples. Although ANS responses are very helpful in differentiating between samples (de Wijk et al., 2012, 2014), this study shows that their association with consumer liking and preference might be limited.

In this study, development of optimum model to predict overall liking and preference was conducted by comparing different combinations of predictors including taste intensity and emotional responses. Among the models predicting, model with taste intensity and EsSense25 (model “D”, Table 3) as predictors were found to have high R^2_{adj}, low RMSE, low *Cp (close to p)*, low AICc and BIC values. However, among the predictor terms, “disgusted” was the only negative emotion with significance in the model “D” in Table 1. Addition of FE analysis to this model resulted in a slight increase in R^2_{adj}, further decrease in RMSE, AICc, and BIC values (model “J” in Table 3). Interestingly, negative expressions such as “fear”, “contempt”, and “disgust” showed significant contributions, along with “joy” (model “J” in Table 1). Even though the *Cp* for this model was a little high, we chose to accept it due to optimization by all other model comparison parameters. Additionally, it provided a balance of positive and negative emotions in the model, which is important to understand overall profile of the consumer behavior. However, addition of ANS response as predictors did not provide any advantage (model “N” in Table 3). Similarly, when developing optimum model for preference rank, the model based on taste intensity, EsSense25, and FE was found to be the best fit due to minimization of *–Log-likelihood,* AICc, and BIC values (model “J” in Table 4).

Comparison of significant predictors between both optimum models, one for overall liking and the other for preference rank, revealed that taste intensity for both models had a lower β value compared to most other emotion terms. This suggests a stronger role of emotions in predicting liking as well as preference as compared to perceived taste intensity. In addition, self-reported “disgusted” and “satisfied” emotions were found to be the strongest predictors in both models. Interestingly, facial expressions associated with “joy” (positive emotion) as well as “disgust” (negative emotion) were found to be significant predictors of overall liking and preference. However, the predictor profile for overall liking (rating) and preference (ranking) data was not entirely similar. More specifically, self-reported “active” emotion and facial expressions associated with “fear” were found to be a significant predictor of liking, but not of preference. The differences between overall liking and preference rank have been reported in previous studies (Lévy & Köster, 1999). Ideally, the sample which is liked the most should be the most preferred. However, Lévy and Köster (1999) found that when participants performed liking as well as preference testing on the same beverage samples, around 30% of the participants did not show coherence between the two tests. As mentioned earlier, liking ratings give an idea of acceptance of the samples, whereas preference rank give insight into choice (Meilgaard et al., 2015). This study further highlights that both liking and preference responses should be considered when evaluating consumer behavior since both the responses might provide different information.

It is worth noting that the self-reported "calm" emotion, although having a positive valence associated with it, was shown to be negatively associated with overall liking and preference rank. In other words, participants liked the samples that made them feel less calm or more aroused, indicating that higher arousal is indicative of higher liking and preference. This is further supported by the observation that participants liked the samples that made them feel more "active", which can be interpreted as another higher arousal emotion with positive valence. Previous research on food images and emotional responses also demonstrated the possible association between low emotional arousal and disliked images (Gil, Rousset, & Droit-Volet, 2009). Similarly, Gutjar et al. (2015a) showed that emotional responses evoked by breakfast drinks and dessert products could be explained in a two-dimensional space, representing a valence (pleasantness/unpleasantness) and an activation/arousal (high/low arousal) dimension. More specifically, while the second dimension is positively associated with high arousal emotions, such as energetic, active, and adventurous, it is negatively associated with low arousal emotions, such as calm and quiet.

In conclusion, perceived taste intensity and emotional responses provide insight into consumer behavior with respect to their overall liking and preference. Moreover, emotional responses measured using a combination of emotion questionnaire and facial expression analysis boost the prediction of overall liking and preferences when compared to individual responses. Since the present study used basic taste solutions as samples, individual variations related to cross-modal interaction and/or product information could be minimized. Based on the results from this study, further studies could be utilized to investigate and understand consumers' liking and preference toward commercial beverages.

Table 1. A list of multiple linear regression models of overall liking for basic taste solutions based on taste intensity, emotion questionnaire (EsSense25), facial expression, and autonomic nervous system (ANS) response

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
A	**Overall Liking**	**Taste intensity**	Taste intensity***	-0.24	0.02
B	**Overall Liking**	**EsSense25**	Disgusted***	-1.03	0.05
			Satisfied***	0.53	0.06
			Good***	0.33	0.09
			Good-natured**	-0.27	0.08
			Secure***	-0.21	0.06
			Active**	0.15	0.05
			Nostalgic*	0.14	0.07
			Calm*	-0.13	0.05
C	**Overall Liking**	**Facial expression**	EV Contempt***	0.72	0.09
			EV Disgust***	-0.56	0.05
			EV Fear***	-0.37	0.10
			EV Sadness***	-0.33	0.10
			EV Surprise***	0.30	0.07
D	**Overall Liking**	**Taste intensity**	Disgusted***	-0.88	0.05
		EsSense25	Satisfied***	0.48	0.06
			Secure**	-0.18	0.06
			Calm***	-0.18	0.05
			Nostalgic**	0.17	0.07
			Good***	0.30	0.09
			Good-natured**	-0.21	0.08
			Active***	0.17	0.05
			Taste intensity***	-0.11	0.01
E	**Overall Liking**	**Taste intensity**	EV Disgust***	-0.53	0.06
		Facial expression	EV Fear***	-0.50	0.10
			EV Contempt***	0.44	0.11
			EV Surprise***	0.25	0.08
			Taste intensity***	-0.18	0.02
			EV Joy***	0.16	0.05
F	**Overall Liking**	**Taste intensity**	Taste intensity***	-0.24	0.02
		ANS			
G	**Overall Liking**	**EsSense25**	Disgusted***	-0.87	0.05
		Facial expression	Satisfied***	0.49	0.05
			EV Contempt***	0.40	0.08
			Good***	0.34	0.08
			EV Disgust***	-0.30	0.05
			Secure***	-0.22	0.06
			EV Fear**	-0.22	0.07
			Good-natured*	-0.18	0.08

Table 1. A list of multiple linear regression models of overall liking for basic taste solutions based on taste intensity, emotion questionnaire (EsSense25), facial expression, and autonomic nervous system (ANS) response (continued)

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
			Active**	0.17	0.05
			Calm**	-0.15	0.05
H	**Overall Liking**	**EsSense25**	Disgusted***	-1.03	0.05
		ANS	Satisfied***	0.53	0.06
			Good***	0.33	0.09
			Good-natured**	-0.27	0.08
			Secure***	-0.21	0.06
			Active**	0.15	0.05
			Nostalgic*	0.14	0.07
			Calm*	-0.13	0.05
I	**Overall Liking**	**Facial expression**	EV Contempt***	0.72	0.09
		ANS	EV Disgust***	-0.56	0.05
			EV Fear***	-0.37	0.10
			EV Sadness***	-0.33	0.10
			EV Surprise***	0.30	0.07
J	**Overall Liking**	**Taste intensity**	Disgusted***	-0.77	0.05
		EsSense25	Satisfied***	0.45	0.05
		Facial expression	EV Disgust***	-0.31	0.05
			EV Contempt**	0.28	0.09
			EV Fear***	-0.27	0.08
			Good**	0.22	0.07
			Secure***	-0.21	0.06
			Calm***	-0.20	0.05
			Active**	0.16	0.05
			Taste intensity***	-0.10	0.01
			EV Joy*	0.08	0.04
K	**Overall Liking**	**Taste intensity**	Disgusted***	-0.88	0.05
		EsSense25	Satisfied***	0.48	0.06
		ANS	Secure**	-0.18	0.06
			Calm***	-0.18	0.05
			Nostalgic**	0.17	0.07
			Good***	0.30	0.09
			Good-natured**	-0.21	0.08
			Active***	0.17	0.05
			Taste intensity***	-0.11	0.01
L	**Overall Liking**	**Taste intensity**	EV Disgust***	-0.53	0.06
		Facial expression	EV Fear***	-0.50	0.10
		ANS	EV Contempt***	0.44	0.11
			EV Surprise***	0.25	0.08

Table 1. A list of multiple linear regression models of overall liking for basic taste solutions based on taste intensity, emotion questionnaire (EsSense25), facial expression, and autonomic nervous system (ANS) response (continued)

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
			Taste intensity***	-0.18	0.02
			EV Joy***	0.16	0.05
M	**Overall Liking**	**EsSense25**	Disgusted***	-0.87	0.05
		Facial expression	Satisfied***	0.49	0.05
		ANS	EV Contempt***	0.40	0.08
			Good***	0.34	0.08
			EV Disgust***	-0.30	0.05
			Secure***	-0.22	0.06
			EV Fear**	-0.22	0.07
			Good-natured*	-0.18	0.08
			Active**	0.17	0.05
			Calm**	-0.15	0.05
M	**Overall Liking**	**Taste intensity**	Disgusted***	-0.77	0.05
		EsSense25	Satisfied***	0.45	0.05
		Facial expression	EV Disgust***	-0.31	0.05
		ANS	EV Contempt**	0.28	0.09
			EV Fear***	-0.27	0.08
			Good**	0.22	0.07
			Secure***	-0.21	0.06
			Calm***	-0.20	0.05
			Active**	0.16	0.05
			Taste intensity***	-0.10	0.01

EV stands for evidence value.
*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Table 2. A list of ordinal logistic regression models of preference rank for basic taste solutions based on taste intensity, emotion questionnaire (EsSense25), facial expression, and autonomic nervous system (ANS) response

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter estimate *(β)*	Standard error (SE)
A	**Preference rank**	**Taste intensity**	Taste intensity***	-0.16	0.01
B	**Preference rank**	**EsSesnse25**	Disgusted***	-0.76	0.06
			Satisfied***	0.31	0.05
			Calm*	-0.12	0.05
C	**Preference rank**	**Facial expression**	EV Disgust***	-0.58	0.06
			EV Anger***	0.30	0.08
			EV Fear**	-0.28	0.09
			EV Surprise***	0.27	0.07
			EV Joy***	0.18	0.04
D	**Preference rank**	**Taste intensity**	Disgusted***	-0.63	0.06
		EsSense25	Satisfied***	0.25	0.06
			Calm**	-0.16	0.05
			Joyful*	0.15	0.08
			Taste intensity***	-0.09	0.02
E	**Preference rank**	**Taste intensity**	EV Disgust***	-0.43	0.06
		Facial expression	EV Anger**	0.24	0.08
			EV Fear*	-0.22	0.09
			EV Surprise**	0.19	0.07
			EV Joy***	0.17	0.04
			Taste intensity***	-0.13	0.01
F	**Preference rank**	**Taste intensity**	Taste intensity***	-0.16	0.01
		ANS			
G	**Preference rank**	**EsSense25**	Disgusted***	-0.68	0.06
		Facial expression	EV Disgust***	-0.33	0.06
			EV Anger***	0.28	0.08
			Satisfied***	0.24	0.06
			Good*	0.16	0.08
			Calm*	-0.14	0.05
			EV Joy**	0.09	0.03
H	**Preference rank**	**EsSesnse25**	Disgusted***	-0.76	0.06
		ANS	Satisfied***	0.31	0.05
			Calm*	-0.12	0.05
I	**Preference rank**	**Facial expression**	EV Disgust***	-0.58	0.06
		ANS	EV Anger***	0.30	0.08
			EV Fear**	-0.28	0.09
			EV Surprise***	0.27	0.07
			EV Joy***	0.18	0.04
			EV Fear**	-0.28	0.09
J	**Preference rank**	**Taste intensity**	Disgusted***	-0.60	0.06

Table 2. A list of ordinal logistic regression models of preference rank for basic taste solutions based on taste intensity, emotion questionnaire (EsSense25), facial expression, and autonomic nervous system (ANS) response (continued)

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter estimate (β)	Standard error (SE)
		EsSense25	EV Disgust***	-0.28	0.06
		Facial expression	EV Anger**	0.24	0.08
			Satisfied***	0.23	0.06
			Calm**	-0.16	0.05
			Good*	0.16	0.08
			EV Joy**	0.10	0.03
			Taste intensity***	-0.08	0.02
K	**Preference rank**	**Taste intensity**	Disgusted***	-0.63	0.06
		EsSense25	Satisfied***	0.25	0.06
		ANS	Calm**	-0.16	0.05
			Joyful*	0.15	0.08
			Taste intensity***	-0.09	0.02
L	**Preference rank**	**Taste intensity**	EV Disgust***	-0.43	0.06
		Facial expression	EV Anger**	0.24	0.08
		ANS	EV Fear*	-0.22	0.09
			EV Surprise**	0.19	0.07
			EV Joy***	0.17	0.04
			Taste intensity***	-0.13	0.01
M	**Preference rank**	**EsSense25**	Disgusted***	-0.68	0.06
		Facial expression	EV Disgust***	-0.33	0.06
		ANS	EV Anger***	0.28	0.08
			Satisfied***	0.24	0.06
			Good*	0.16	0.08
			Calm*	-0.14	0.05
			EV Joy**	0.09	0.03
N	**Preference rank**	**Taste intensity**	Disgusted***	-0.60	0.06
		EsSense25	EV Disgust***	-0.28	0.06
		Facial expression	EV Anger**	0.24	0.08
		ANS	Satisfied***	0.23	0.06
			Calm**	-0.16	0.05
			Good*	0.16	0.08
			EV Joy**	0.10	0.03
			Taste intensity***	-0.08	0.02

EV stands for evidence value.
*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Table 3. Model comparison parameters for predicting overall liking based on taste intensity, emotion questionnaire (EsSense25), facial expression (FE), and autonomic nervous system (ANS) response

Model code	Dependent variable	Independent variables	R^2_{adj}	RMSE	*Cp*	*p*	AIC	BIC
A	**Overall liking**	**Taste intensity**	0.20	2.06	2.00	2	4368.51	4383.27
B	**Overall liking**	**EsSense25**	0.44	1.71	12.01	9	4002.59	4051.65
C	**Overall liking**	**FE**	0.21	2.03	9.02	6	4351.46	4385.84
D	**Overall liking**	**Taste intensity, EsSense25**	0.48	1.66	11.21	10	3942.23	3996.17
E	**Overall liking**	**Taste intensity, FE**	0.30	1.92	9.12	7	4229.38	4268.63
F	**Overall liking**	**Taste intensity, ANS**	0.20	2.06	-0.33	2	4368.51	4383.27
G	**Overall liking**	**EsSense25, FE**	0.48	1.65	16.91	11	3934.44	3993.26
H	**Overall liking**	**EsSense25, ANS**	0.44	1.71	11.40	9	4002.59	4051.65
I	**Overall liking**	**FE, ANS**	0.21	2.03	10.60	6	4351.46	4385.84
J	**Overall liking**	**Taste intensity, EsSense25, FE**	0.50	1.62	17.76	12	3892.88	3956.58
K	**Overall liking**	**Taste intensity, EsSense25, ANS**	0.48	1.66	10.75	10	3942.23	3996.17
L	**Overall liking**	**Taste intensity, FE, ANS**	0.30	1.92	9.36	7	4229.38	4268.63
M	**Overall liking**	**EsSense25, FE, ANS**	0.48	1.65	19.59	11	3934.44	3993.26
N	**Overall liking**	**Taste intensity, EsSense25, FE, ANS**	0.50	1.62	19.85	12	3892.88	3956.58

RMSE, *Cp*, *p*, AICc, and BIC stand for Root Mean Square Error, Mallow's *Cp*, total significant predictors including intercept, corrected Aikaike Information Criterion, and Bayesian Information Criterion, respectively.

Table 4. Model comparison parameters for predicting preference rank based on taste intensity, emotion questionnaire (EsSense25), facial expression (FE), and autonomic nervous system (ANS) response

Model code	Dependent variable	Independent variables	R^2	*-Log-likelihood*	AICc	BIC
A	**Preference rank**	**Taste intensity**	0.04	1569.16	3148.37	3172.95
B	**Preference rank**	**EsSense25**	0.09	1502.00	3018.12	3052.5
C	**Preference rank**	**FE**	0.04	1579.03	3176.24	3220.41
D	**Preference rank**	**Taste intensity, EsSense25**	0.10	1482.82	2983.81	3027.98
E	**Preference rank**	**Taste intensity, FE**	0.06	1539.54	3099.3	3148.35
F	**Preference rank**	**Taste intensity, ANS**	0.04	1569.16	3148.37	3172.95
G	**Preference rank**	**EsSense25, FE**	0.09	1485.79	2993.84	3047.78
H	**Preference rank**	**EsSense25, ANS**	0.08	1502.00	3018.12	3052.5
I	**Preference rank**	**FE, ANS**	0.04	1579.03	3176.24	3220.41
J	**Preference rank**	**Taste intensity, EsSense25, FE**	0.10	1472.72	2969.75	3028.57
K	**Preference rank**	**Taste intensity, EsSense25, ANS**	0.10	1482.82	2983.81	3027.98
L	**Preference rank**	**Taste intensity, FE, ANS**	0.06	1539.54	3099.3	3148.35
M	**Preference rank**	**EsSense25, FE, ANS**	0.09	1485.79	2993.84	3047.78
N	**Preference rank**	**Taste intensity, EsSense25, FE, ANS**	0.10	1472.72	2969.75	3028.57

AICc and BIC stand for adjusted corrected Aikaike Information Criterion and Bayesian Information Criterion, respectively.

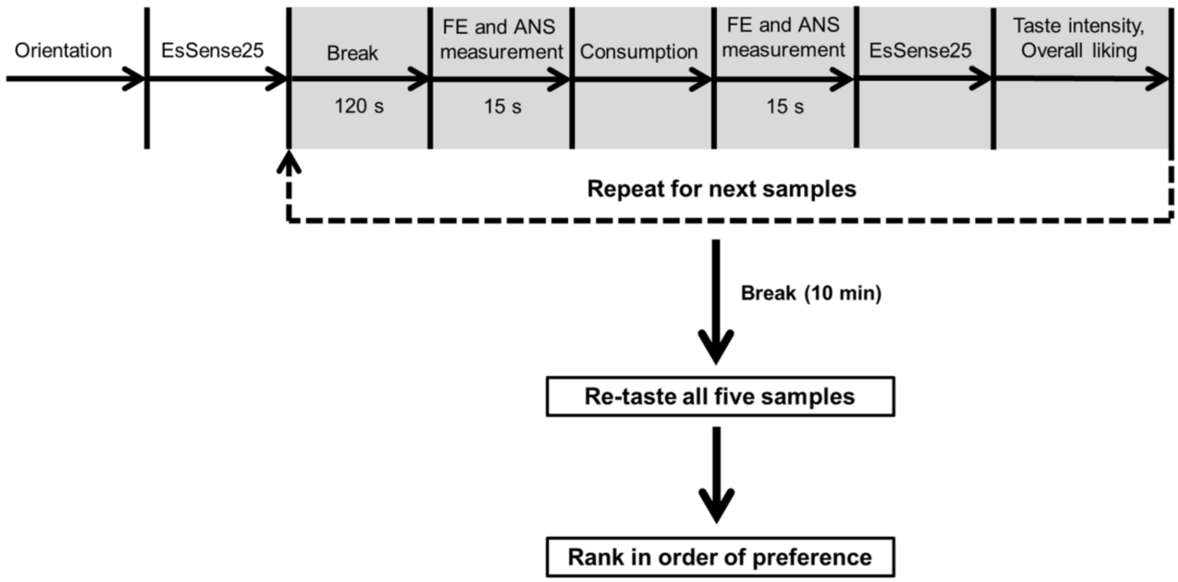

Figure 1. Overall scheme of experimental procedure. FE and ANS stand for facial expression and autonomic nervous system (ANS) response, respectively.

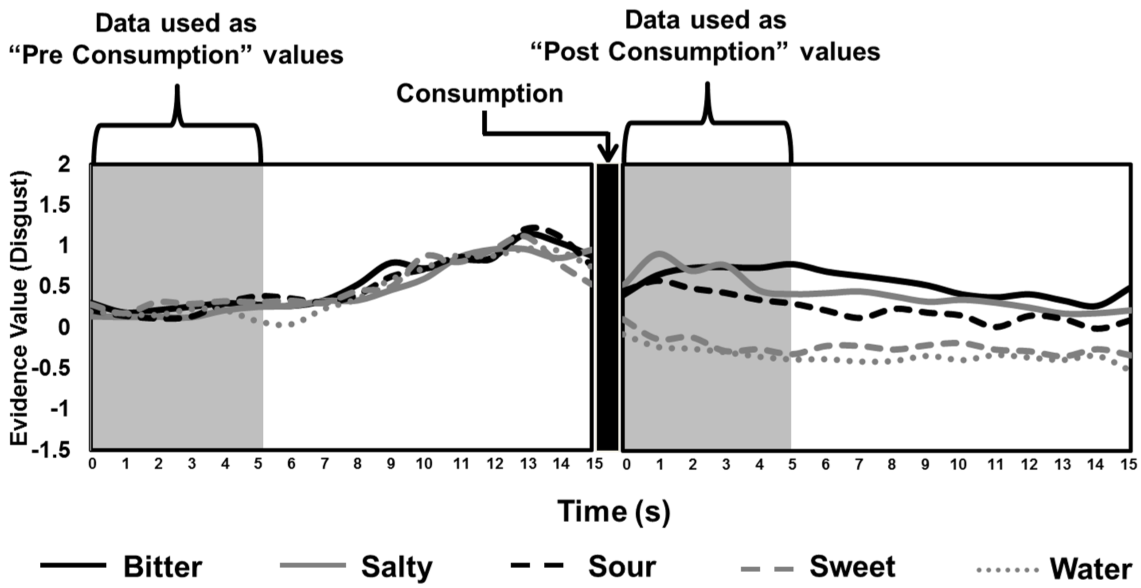

Figure 2. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before (A) and after (B) consumption of bitter, salty, sour, and sweet-tasting solutions at high concentration level, as well as water as a control.

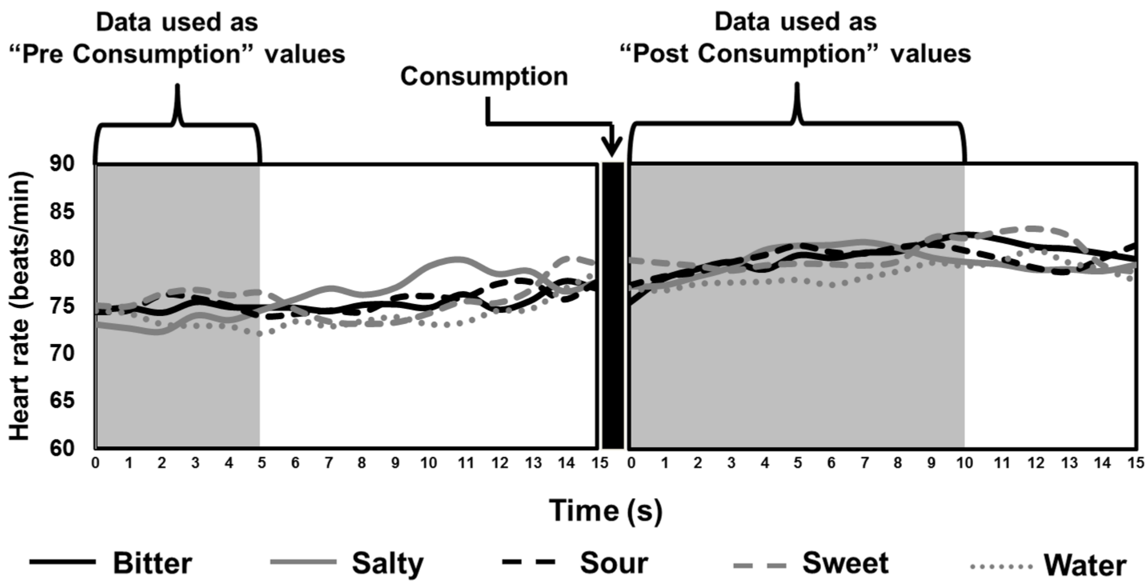

Figure 3. Changes in heart rate value (beats/min) over 15 s before (A) and after (B) consumption of bitter, salty, sour, and sweet-tasting solutions at high concentration level, as well as water as a control.

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Objective 4

Using both emotional responses and sensory attribute intensities to predict consumer liking and preference toward vegetable juice products

Abstract

Our previous research found that a combination of sensory attribute intensity and emotional responses helps in achieving better understanding of consumer acceptance and preference for basic taste solutions. By applying this finding to beverage samples, this study aimed to develop an optimum model of predicting either overall liking or preference of vegetable juice products based on sensory attribute intensities and emotional responses. One hundred participants (50 females) were asked to look at, smell, and taste five vegetable juice samples. Their emotional responses to each sample were measured through a combination of self-reported emotions, facial expressions, and autonomic nervous system (ANS) responses. Their overall liking and perceived intensities of sensory attributes were also measured. After a break, participants re-tasted all samples and ranked them according to preference. The results showed that emotional responses measured using a self-reported emotion questionnaire and facial expression analysis, along with perceived sensory intensities, performed best in predicting overall liking, while ANS measures made only limited contribution. However, the amount of overall variation attributed to these independent predictors was low in terms of preference rank. Finally, a majority of independent predictors showed neither differences between test and retest sessions nor interactions between session and test product over a period of two weeks. In conclusion, our findings extend the previous notion that a combination of sensory intensities and emotional responses can better predict consumer acceptance of commercially-available vegetable juice products.

Keywords: Consumer acceptance; Consumer behavior; Sensory perception; Emotion; Facial expression; Autonomic Nervous System Response; Vegetable juice

1. Introduction

Consumer behaviors, especially those associated with acceptance of food/beverage products, are greatly influenced by their complex cognitive processing of multisensory perception and emotional experience (Berridge, 1996; Hirschman & Holbrook, 1982). Although it is difficult to draw a direct relationship between sensory intensities and liking due to variation in attribute type and food products being tested, attribute intensities are often considered for predicting consumer liking and/or preference toward food/beverage products (Crist, Duncan, Arnade, Leitch, O'Keefe, & Gallagher, 2018; Samant, Chapko, & Seo, 2017). Earlier studies showed that food/beverage-evoked emotions are related to either consumer liking of or preference for the food/beverage products: for example, blackcurrant squashes (Ng, Chaya, & Hort, 2013), breakfast drinks (de Wijk, He, Mensink, Verhoeven, & De Graaf, 2014), coffee and tea (Pramudya & Seo, 2018), fruit and vegetable juices (Waehrens, Grønbeck, Olsen, & Byrne, 2018).

Food/beverage-evoked emotion, defined as "a brief but intense physiological and/or mental reaction to a food or beverage item" (King & Meiselman, 2010; Kenney & Adhikari, 2016), is a relatively newer concept that has gained rapid interest over the past decade. However, measuring food/beverage evoked emotions still remains a challenge for researchers. Different methodologies developed over the years for this purpose can be broadly classified into two major types, namely, explicit (or "direct") and implicit (or "indirect") methods. Explicit methods are comprised of self-reported ratings on questionnaires using verbal descriptor terms (e.g., EsSense Profile®; King & Meiselman, 2010) or non-verbal descriptor terms (e.g., the emoji facial scale; Swaney-Stueve, Jepsen, & Deubler, 2018). Common implicit methods used to measure emotional responses are facial expression (FE) analysis and autonomic nervous system (ANS) response analysis. FE analysis is typically carried out by using relevant computer software with built-in information on changes in human facial expression produced by different emotions (iMotions, 2017; Tian, Kanade, & Cohn, 2005). ANS response analysis measures physiological changes in the human body, in particular those in response to food/beverage-evoked emotions (Kreibig, 2010; Lagast, Gellynck, Schouteten, De Herdt, & De Steur, 2017). These changes can mainly be observed in electro-dermal activity (EDA) of the skin measured as skin conductance response (SCR), cardiovascular activity measured as heart rate (HR) or heart rate variability (HRV), skin temperature (ST), and pupil dilation (Kenney & Adhikari, 2016; Lagast et al., 2017; Spinelli & Niedziela, 2016). These methods can be used either individually or in combination to measure food/beverage-evoked emotional responses.

Recently, Lagast et al. (2017) reviewed 70 research articles on measurements of food/beverage-evoked emotions dating from the early 2000's until June 2016. Interestingly, while use of explicit methods for measuring food/beverage-evoked emotions have been described in 52 out of 70 articles (74.3%), implicit methods or a combination of explicit and implicit methods have been employed in only 12 (17.1%) and 6 (8.6%) articles, respectively. Kaneko, Toet, Brouwer, Kallen, and van Erp (2018) reported a similar trend. More than 60% of the reported methods for measuring food/beverage-evoked emotions were based on self-reported, subjective ratings across 101 peer-reviewed articles relevant to this topic. While the apparent dominance of explicit over implicit methods is due to their ease of use, simple handling, and easy processing of obtained data, some researchers suggest that explicit methods could be cognitively biased since they rely on translation of emotional experiences into verbal/non-verbal terms

(Kaneko et al., 2018; Lagast et al., 2017; also see Spinelli & Niedziela, 2016). In other words, since explicit methods are dependent on consumers' retrospection of their experience with food/beverage products followed by expressing it using descriptor terms, this procedure might lead to loss of some information during translation from experience to expression. The advantage of implicit methods, on the contrary, is that facial expressions and ANS responses are non-self-reported involuntary reactions to emotions. Moreover, they can be measured even while consumers are engaged in sniffing or looking at the food/beverage products without having to retrospect their experience and translate it into verbal/non-verbal terms (Lagast et al., 2017). Kreibig (2010) provided an extensive review suggesting that emotional responses could be manifested as changes in ANS responses such as HR, SCR, FT, and HRV. However, ANS measures are considered to serve as better indicators of emotional valence, i.e., arousal and valence, compared to discrete emotions such as fear or joy (Köster & Mojet, 2015; Mauss & Robinson, 2009; Spinelli & Niedziela, 2016). In addition, Meiselman (2015) reported that facial expression and ANS responses measure a small number of emotions and they might not measure all emotions relevant to a test product. Previous research also suggests that facial expressions measure negative emotions more reliably compared to positive emotions (Zeinstra, Koelen, Colindres, Kok, & de Graaf, 2009). Considering such pros and cons of both explicit and implicit measures, Samant et al. (2017) used a combination of explicit and implicit techniques for measuring evoked emotions, along with sensory attribute perception, to develop prediction models of either consumer liking or preference toward basic taste solutions. The results from that study suggested that a combination of self-reported emotions (explicit) and facial expressions (implicit), along with taste intensity, can better predict overall liking and preference rank toward basic taste solutions when compared to individual measures.

Previous research on using combined explicit and implicit methods as predictors of consumer acceptance and preference is limited, thereby posing a knowledge gap. Firstly, contribution of each emotional measurement method combined with sensory attribute intensities has not been fully explored. For example, although a previous study (Samant et al., 2017) included sensory intensity along with emotional responses for prediction, only taste intensity was included because of the nature of the basic taste solutions, and the roles of other sensory attributes such as appearance, aroma, flavor, and mouthfeel are still not clear. Secondly, and more importantly, most previous research did not consider a test-retest comparison of emotional responses with respect to predicting consumer behavior. From an applied-emotion research standpoint, it is important to show the stability of any proposed novel method for predicting consumer behavior to justify its practical application in realistic contexts.

In an attempt to addressing the above limitations, the objective of this study was to use the proposed method on basic taste solutions (Samant et al., 2017) and extend its application to commercial beverage samples such as vegetable juice products. Vegetable juices were chosen as the target product because they are becoming increasingly popular due to their high nutritional content and health-promoting characteristics (Shishir & Chen, 2017); since many vegetable-juice products commercially available in a market are composed of mixed vegetables, mixed-vegetable juices were used in this study. In particular, the current study was aimed at developing prediction models of either consumer acceptance or preference toward commercial vegetable juice products using a combination of emotional responses and sensory attribute perceptions as independent variables. Herein, emotional responses were measured using both explicit (a self-reported emotion questionnaire) and implicit (facial expression analysis and ANS response analysis) techniques. In addition, using multiple sensory attributes intensities (e.g., color, aroma, flavor, saltiness, and viscosity, etc.) for predicting consumer acceptance and preference toward vegetable juice products were included. Furthermore, this study was designed to address test-retest comparisons of all measured variables employed in this study.

2. Materials and Methods

The protocol used in this study was approved by the Institutional Review Board of the University of Arkansas (Fayetteville, AR). Prior to participation, the experimental procedure was explained and a written consent indicating voluntary participation was obtained from each participant.

2.1 Participants

A total of 100 healthy adults [50 females, mean age ± standard deviation (SD) = 41 ± 13 years] with no known food allergies or clinical histories of major disease were recruited through the University of Arkansas Sensory Service Center database that included consumer profiles of 6,200 Northwest Arkansas residents. To minimize potential influences of mental stress on intensity perception and acceptability (Samant, Wilkes, Odek, & Seo, 2016), it was ensured that none of the participants had a high level of chronic stress, i.e., their scores on the 10-item Perceived Stress Scale (PSS) (Cohen, Kamarch, & Mermelstein, 1983) were all lower than 25 points. In addition, participants were asked to rate how often they drank vegetable juices/blends on an 8-point scale (1: never, 2: less than once a month. 3: one-three times month, 4: one-two times a week, 5: three-four times a week, 6: five-six times a week, 7: once a day, 8: two or more times a day) and how much they liked drinking vegetable juice products on a 9-point hedonic scale ranging from 1 (dislike extremely) to 9 (like extremely). Participants who selected "never" and "dislike extremely" on the former and latter questions, respectively, were not included in the study.

2.2. Sample preparation

Five commercially-available mixed vegetable juice products were purchased from local markets in Fayetteville, AR, USA: VJA (365® Everyday Value Organic Juice Vital Veggie, Whole Foods Market, Austin, TX, USA), VJB (Great Value™ Vegetable Juice, Wal-Mart Stores, Inc., Bentonville, AR, USA), VJC (R.W. Knudsen Family Organic Very Veggie® Low Sodium, Knudsen & Sons, Inc., Chico, CA, USA), VJD (V8® Original Low Sodium Juice, Campbell Soup Co., Camden, NJ, USA), and VJE (V8® Original Juice, Campbell Soup Co., Camden, NJ, USA).

These five products were chosen as test samples because they showed different profiles of sensory attributes based on preliminary testing. To ensure whether the five mixed-vegetable juice products differed with respect to sensory attributes, a descriptive sensory analysis was conducted. Eight professionally-trained panelists at the University of Arkansas Sensory Service Center (Fayetteville, AR, USA) characterized 30 sensory attributes (1 appearance, 6 aromas, 4 basic tastes, 9 flavors, 4 mouth0feeling, and 6 after tastes) and rated attribute intensities in duplicate on scales ranging from 0 to 15 with 0.1 increments. Each sample was served at refrigerated temperature (approximately, 4 °C) in 60-mL soufflé cups (Pettus Office Products, Little Rock, AR, USA) identified by a 3-digit code. Each of the five samples was randomly presented to the panelists, one after another. During a five-min break between sample presentations, spring water (Mountain Valley, Hot Springs, AR, USA) and unsalted crackers (Nabisco Premium, Mondelēz International, East Hanover, NJ, USA) were provided for participants' palate cleansing. As shown in Supplementary Table 1, the 5 samples were found to differ significantly with respect to 25 sensory attributes (for all, $P < 0.05$).

2.3. Measurements of sensory attribute intensities and overall liking

Participants rated their perceived color-intensities of test samples on 15-cm line scales ranging from 0 (extremely light) to 15 (extremely dark). They also rated intensities of perceived aroma, overall flavor, sweetness, sourness, bitterness, and saltiness on 15-cm line scales ranging from 0 (extremely weak) to 15 (extremely strong). Since all test samples were composed of mixed vegetables and the participants had not been professionally trained with respect to sensory evaluation, overall aspects, not specific attributes (e.g., tomato aroma), of aroma or flavor perception were evaluated (i.e., overall aroma or overall flavor). In addition, participants rated perceived viscosity of the samples on 15-cm line scales ranging from 0 (not at all viscous) to 15 (extremely viscous). Finally, levels of overall liking of the samples were measured using traditional 9-point hedonic scales ranging from 1 (dislike extremely) to 9 (like extremely).

2.4. Measurement of emotional responses

2.4.1. Explicit method

Self-reported emotion questionnaire (EQ)

EsSense25 (25 items; Nestrud, Meiselman, King, Lesher, & Cardello, 2016), a reduced version of the EsSense Profile® (39 items; King & Meiselman, 2010) was used to measure self-reported emotions. Participants rated each item of the EsSense25 on a 5-point scale ranging from 1 (not at all) to 5 (extremely). The 25 emotion terms were presented in alphabetical order. While some emotions toward food samples were previously found to differ with the order of emotion terms (i.e., alphabetical order versus random order), the influence of emotion term order was smaller in a rating scale than in a Check-All-That-Apply (CATA) scale (King, Meiselman, & Carr, 2013).

2.4.2. Implicit method

Facial expression (FE) analysis

Facial expression software (version 6.1, iMotions, Inc., MA, USA) was used for recording and analyzing facial expressions. At a sampling rate of 102.4 Hz, this software measured presence of 7 basic universal expressions of human emotions (i.e., joy, anger, surprise, fear, contempt, disgust, and sadness) and reported "evidence value" (EV) associated with each emotion. EVs represent logarithmically (base 10) the odds of an emotion being present in a participant's facial expression when compared to his or her neutral state (iMotions, 2017; Samant et al., 2017). For example, a positive (or negative) EV of q for the "fear" emotion, when evaluated by a human coder, indicates that expression is 10^q times more (or less) likely to be categorized as fearful compared to a neutral state (iMotions, 2017).

Autonomic nervous system (ANS) response analysis

ANS responses, specifically heart rate (HR), skin temperature (ST), and electro-dermal activity (EDA) of the skin, were measured using a flexible and non-invasive sensing platform (Burns et al., 2010), a SHIMMER™ sensor (SHIMMER™, Dublin, Ireland). EDA consists of two main components: tonic EDA and phasic EDA. While tonic EDA is related to slower responses that are spread over a longer time span (e.g., few minutes after onset of stimuli), phasic EDA has shorter time spans and is more event-related, including quick responses to stimuli (Samant et al., 2017). Since emotions are considered as quick response to stimuli, phase EDA [referred to as skin conductance response (SCR)] was measured.

Both HR (unit: beats/minute) and SCR (unit: µSiemens) were measured at a sampling rate of 102.4 Hz. HR was measured by placing an electrode on the proximal phalanges of the participants' ring finger, while SCR was measured by placing two Velcro-strap electrodes on the proximal phalanges of index and middle fingers of the non-dominant hand of the participant. In addition, ST (unit: °C) was measured every 0.2 s using an eSense Skin Temperature Sensor for Android devices (Mindfield® Biosystems Ltd., Gronau, Germany) placed on the palm of a participant's non-dominant hand (Samant et al., 2017).

2.5. Procedure

2.5.1 Instruction and experimental set-up

The overall scheme of experimental procedure followed in this study is described in Figure 1. Prior to beginning the study, participants were asked to sit comfortably, and the experimental procedure was carefully explained. Each participant was asked to rate 25 emotions on the EsSense25 scale based on how much of each emotion she/he felt at that moment (see above). A camera (Logitech Europe S.A., Nijmegen, Netherlands) was placed in front of the participant to measure facial expressions. Camera location and chair height was adjusted to obtain a clear view of the participant's face. 70% (v/v) isopropanol (PL developments, Clinton, SC, USA) was used to clean the non-dominant hand of the participant. In addition, a conductive electrode cream (Synapse®, Kustomer Kinetics, Inc., Arcadia, CA, USA) was gently spread over the proximal phalanges of index and middle finger on the non-dominant hand of the participant. As described above, electrodes were attached to the non-dominant hand of the participant to measure SCR, HR, and ST.

2.5.2. Test session

Each participant was asked to evaluate five samples in a randomized sequential monadic fashion. Approximately 45-mL of each sample was presented in a 60-mL soufflé cup identified with a 3-digit code. The participant was first asked to look at the sample and evaluate its appearance. FE and ANS responses were measured for 15 s before the participant started looking at the sample ("pre-appearance" time window) and for 10 s while he/she was visually evaluating the appearance of the sample ("appearance" time window). The participant was then asked to rate the intensity of color of the sample.

The participant was next asked to sniff the aroma of the sample. FE and ANS responses were also measured for 15 s before participants started smelling the sample ("pre-aroma" time window) and for 10 s while he/she was sniffing it ("aroma" time window). The participant was then asked to rate the intensity of aroma of the sample.

Finally, the participant was asked to pour the entire sample in his/her mouth and swallow while constantly looking at the camera. FE and ANS responses were measured for 15 s before participants poured the sample in her/his mouth ("pre-consumption" time window) and for 15 s after she/he swallowed the sample ("post-consumption" time window). Following that, the participant was asked to rate the intensities of overall flavor, sweetness, bitterness, sourness, saltiness, and viscosity, as well as levels of overall liking as described in Section 2.3. Participants were asked again to rate each emotion on EsSense25, to measure how the sample made her/him feel. A two-min break was given between samples. It should be noted that each participant was instructed to keep her/his hand movement to a minimum and advised against talking during the entire length of the study to avoid noise in the FE and ANS response measures.

After tasting all five samples during a test session, each participant was given a break of about ten minutes. The participant was next taken to a different room and asked to re-taste the five samples; all samples were coded with different three-digit codes to minimize potential recollection or learning-related influences. After tasting all five samples, the participant was asked to rank the samples in order of preference (1: most preferred; 5: least preferred).

2.5.3. Retest session

To verify the stability of the proposed method, 30 (14 females; mean age ± SD = 39 ± 10 years) out of the 100 participants who had completed the study were asked to return 2 weeks later for a retest session. Those participants were randomly chosen. The samples and procedure during the retest were similar to those of the test session explained earlier, with the only difference that participants were not asked to move to a different room to perform the preference test. In other words, they were asked to complete the preference test in the same room. The purpose of a retest session was two-fold: 1) to ensure that the proposed method yielded reproducible results and 2) to make sure that a change of context, i.e., movement to a different room during preference testing, did not influence the results from the preference rank test.

2.6. Data analysis

2.6.1. Explicit method: Self-reported emotions

To obtain evoked emotions by samples, each participant's baseline rating of each emotion term, i.e., its rating prior to beginning the study, was subtracted from the rating after consumption of each sample. The subtracted values were used for subsequent statistical analysis.

2.6.2. Implicit methods: Facial expression (FE) analysis and autonomic nervous system (ANS) response analysis

Prior to statistical analysis, it was tested how FE and ANS responses changed in the time-windows of pre-appearance, appearance, pre-aroma, aroma, pre-consumption, and post-consumption. As an example, the disgust emotion exhibited a considerably stable response during the last 5 s in the pre-appearance, pre-aroma and pre-consumption time windows (see supplementary Figures 1 to 3). Heart rate exhibited a similar trend (see supplementary Figures 4 to 6). We therefore decided to consider the last 5 s of pre-appearance, pre-aroma, and pre-consumption time windows as “Pre-Appearance”, “Pre-Aroma” and “Pre-Consumption” values, respectively, for FE and ANS response for each sample.

In the time windows of appearance, aroma, and post-consumption, while disgust emotion exhibited maximum variation in the first 5 s (supplementary Figures 1 to 3), HR exhibited its maximum change over the first 10 s (supplementary Figures 4 to 6), possibly because ANS responses have slower onset compared to facial expressions (Danner, Sidorkina, Joechl, & Duerrschmid, 2014). Since similar results for basic taste solutions were found in a previous study (Samant et al., 2017), we decided to use first 5 s of FE and first 10 s of ANS responses from the time windows of appearance, aroma and post-consumption (referred as “Appearance”, “Aroma” and “Post-Consumption” values) for each sample.

Finally, average data exhibited by FE responses obtained during “Pre-Appearance”, “Pre-Aroma” and “Pre-Consumption” stage was subtracted from average data obtained during “Appearance”, “Aroma” and “Post-Consumption” stage, respectively, of each sample, for all participants. These values are referred as FE (APP), FE (AR) and FE (PTC), respectively. Similarly, average data exhibited by ANS responses obtained during “Pre-Appearance”, “Pre-Aroma” and “Pre-Consumption” stage was subtracted from average data obtained during “Appearance”, “Aroma” and “Post-Consumption” stage, respectively, of each sample, for all participants. These values are referred as ANS (APP), ANS (AR) and ANS (PTC), respectively.

2.6.3. Statistical analysis

JMP® Pro (version 14.0, SAS Institute Inc., Cary, NS) was used to conduct both a stepwise multiple linear regression analysis and a stepwise ordinal logistic regression analysis to predict overall liking and preference rank, respectively. In other words, overall liking and rank were used as the dependent variables (fitted separately) and all other variables (8 sensory attribute intensities, 25 self-reported-emotions on EsSense25, 7 EVs of basic emotions in FE measure, SCR, HR, and ST values in ANS measure) were chosen as independent variables. It should be noted that all continuous variables were standardized and then used for regression analysis. A total of 15 statistical models were constructed for each dependent variable, i.e., overall liking or preference rank, to determine the predictive values of the independent variables and to find an optimum model. As described in previous studies (Samant et al., 2017; Samant & Seo, 2018), a *P*-value stopping criterion was chosen for optimum variable selection; probabilities for a predictor to enter and leave the model were set at 0.25 and 0.05, respectively. Parameter estimates (β) for each predictor in the model, along with their corresponding standard errors and levels of significance were reported. By definition, in multiple linear regression, β values represent an estimate of change in dependent variable that, in turn, corresponds to a unit increase in that independent variable while all other independent variables are held constant (Klimberg & McCullough, 2013, Chapters 4 and 10). However, in ordinal logistic regression, a negative value of β represents a probability increase in the higher numbered response categories (i.e., "less preferred" in this study). Predictors in all the models in this study had variable inflation factors (VIF) < 3, indicating low multicollinearity among the predictors (Klimberg & McCullough, 2013, Chapters 4 and 10). Models constructed for overall liking using a multiple linear regression approach were compared using adjusted R^2 (R^2_{adj}), root mean square error (RMSE), Mallows' C*p*, total number of predictors in the model (p), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC). These parameters have been extensively used in the past for multiple linear regression model comparison (Montgomery, Peck, & Vining, 2015, Chapters 3 and 10), and in general lower values of C*p*, AICc, and BIC are preferred (Montgomery et al., 2015). Models constructed for preference rank using a stepwise ordinal logistic regression approach were compared using R^2, *-log-likelihood*, AICc, and BIC. The *-log-likelihood* estimates are often used as model comparison measures for ordinal data, with higher values considered to represent better fit (JMP®, 2013).

Data for 30 participants who had completed both test and retest sessions was used to analyze test-retest comparison. A repeated measures analysis of variance (RM-ANOVA), treating “session” and “product” as within-participant factors, was performed using SPSS 24.0 for Windows™ (IBM SPSS Inc., Chicago, IL, USA). If a sphericity assumption was violated, as could be indicated by the Mauchly’s sphericity test, the degrees of freedom were adjusted by using the “Greenhouse-Geisser” correction. In addition, to measure effect size, a partial eta squared ($\eta\rho^2$) value was used, with partial eta squared values of 0.01, 0.06, and 0.14 considered small, medium, and large effect sizes, respectively (Velasco, Salgado-Montejo, Marmolejo-Ramos, & Spence, 2014). Since we are interested in measuring consistency of measured responses, we focused on “session x product” interactions. If a significant interaction was indicated by the RM-ANOVA, a paired *t*-test was performed to compare means from “test” and “retest” sessions for each product. In addition, a Wilcoxon signed-rank test was performed to compare preference ranks between “test” and “retest” sessions for each product. A statistical significance was determined at $P < 0.05$.

3. Results

3.1. Relationships of sensory attribute intensities with overall liking and preference rank

As described above, out of 30 sensory attributes evaluated by trained panelists, 25 attributes were found to differ significantly among the 5 mixed-vegetable juice samples (Supplementary Table 1). In addition, Supplementary Table 2 shows that the five mixed-vegetable juice samples were found to differ significantly with respect to all eight attribute intensities rated by untrained consumers (for all, $P < 0.05$). Both trained panelists and untrained consumers evaluated that sample VJA showed higher intensities with respect to dark color and viscosity than did the other samples. In addition, both types of panelists evaluated that sweetness intensity of sample VJC was significantly lower compared to samples VJB and VJE. The two low-sodium samples, VJC and VJD, were rated significantly lower in saltiness intensity compared to other samples.

Those variations in sensory attribute intensities were found to affect overall liking and preference toward vegetable juice samples. As shown in model “A” of Table 1, vegetable juice samples with higher intensities of sweetness and flavor and lower intensities of bitterness and sourness were more likely to be accepted. Table 2 (model “A”) shows that vegetable juice samples with a higher intensity of saltiness and lower intensities of sourness and bitterness were more likely to be preferred.

3.2. Relationships of emotional responses with overall liking and preference rank

3.2.1. Explicit method

Self-reported emotion questionnaire (EQ)

As shown in model “B” of Table 1, while positive emotions such as “satisfied” and “happy” exhibited a positive relationship with overall liking, negative emotions such as “bored” and “disgusted” exhibited a negative relationship with overall liking. In addition, “guilty” emotion showed a positive association with overall liking.

Relationship between EQ and preference rank was less evident even though self-reported “satisfied” responses were found to be associated with higher preferred ranks (model “B” in Table 2).

3.2.2. Implicit method

Facial expression (FE) analysis

As shown in model “C” in Table 1, higher evidence values (EVs) of “surprise” were observed when participants looked at the sample and during post-consumption, i.e., EV Surprise (APP) and EV Surprise (PTC), respectively, associated with higher liked samples. In addition, lower EVs of “disgust” [EV Disgust (PTC)] and “sadness” [EV Sadness (PTC)] during post-consumption were associated with samples that were more liked among participants. Higher EVs of “sadness” when looking at the sample [EV Sadness (APP)] and higher EVs of “contempt” during post-consumption [EV Contempt (PTC)] were found to be associated with higher liked samples. Contrary to our expectation, lower EVs of “joy” during post-consumption was associated with higher liked samples.

Association of FE with preference rank was limited (model “C” in Table 2). Higher EVs of “contempt” during post-consumption [EV Contempt (PTC)] were associated with more preferred samples.

ANS response analysis

ANS responses showed limited associations with overall liking (model “D” in Table 1). In other words, HR, SCR, and FT measured while looking at (APP) or smelling (AR), or after tasting (PTC) were found to show no significant contributions to predicting overall liking of vegetable juice samples (for all, $P > 0.05$).

SCR measured during aroma evaluation, i.e., SCR (AR), was associated with more preferred samples (model “D” in Table 2). Other ANS responses, however, showed no significant contributions to the prediction model of preference rank.

3.3. Optimal model selection

Tables 3 and 4 provide model performance parameters for each model constructed with respect to overall liking and preference rank, respectively. As shown in Table 3, a multiple linear regression model “K” to predict overall liking, using a combination of sensory attribute intensity (SAI), self-reported emotions (EQ), and facial expressions (FE), was found to be the optimum model since it produced the highest R^2_{adj} (0.61), the lowest RMSE (0.63), and lower values in term s of AICc (972.29) and BIC (1050.78). As shown in model “K” of Table 5, all sensory attribute intensities served as significant predictors for this model: sourness ($\beta = -0.19$, $P < 0.001$), bitterness ($\beta = -0.18$, $P < 0.001$), sweetness ($\beta = 0.24$, $P < 0.001$), saltiness ($\beta = 0.07$, $P <$

0.05), and flavor (β = 0.11, P < 0.001). In addition, self-reported emotions of "disgusted" (β = −0.32, P < 0.001), "satisfied" (β = 0.18, P < 0.001), "bored" (β = −0.12, P < 0.001), "happy" (β = 0.12, P < 0.01), "secure" (β = −0.11, P < 0.01), and "interested" (β = 0.07, P < 0.05) were found to be significant predictors of overall liking. Finally, based on facial expression analysis, significant predictors were: EV Surprise (PTC) (β = 0.14, P < 0.001), EV Sadness (PTC) (β = −0.11, P < 0.001), EV Surprise (APP) (β = 0.09, P < 0.01), EV Sadness (APP) (β = 0.07, P < 0.05), EV Anger (APP) (β = - 0.09, P < 0.01), and EV Anger (AR) (β = 0.07, P < 0.05).

To predict preference rank, five models "F", "G", "K", "L" and "M" were very close in terms of model performance parameters (Table 4). However, since model "M" using SAI, FE, and ANS measures exhibited a slightly better performance, it could be considered as the optimum model. In particular, model "M" produced the highest R^2 (0.04), the lowest -*LogLikelihood* (775.03), and lower values with respect to AICc (1568.42) and BIC (1605.99). Significant predictors for model "M" were saltiness (β = 0.44, P < 0.001), sourness (β = -0.29, P < 0.01), and bitterness (β = -0.21, P < 0.05) intensities along with EV Contempt (PTC) (β = 0.18, P < 0.05) and SCR (AR) (β = 0.21, P < 0.05) (model "M" in Table 5).

3.4. Test-retest comparison

3.4.1. Comparison of test and retest sessions in terms of dependent and independent variables

Test-retest comparisons were determined with respect to dependent (i.e., overall liking) and independent variables (i.e., sensory attribute intensity, self-reported emotion, facial expression, and ANS response) measured during "test" and "retest" sessions. As described previously, this analysis used data from 30 participants who completed both test and retest sessions. Among sensory attribute intensities, significant interaction between session and product was found for color intensity [F (4, 116) = 2.79, P = 0.03, $\eta\rho^2$= 0.09]. As shown in Figure 2, a paired t-test revealed that the VJD sample was rated to be darker on test day than on retest day [t (29) = 3.29, P = 0.003]. This trend was not observed for any other samples (P > 0.05 for all; for details, see Supplementary Table 3).

Significant interaction between session and product was observed for self-reported emotions such as "active" [F (4, 116) = 2.63, P = 0.04, $\eta\rho^2$= 0.08], "disgusted" [F (2.98, 86.41) = 3.83, P = 0.01, $\eta\rho^2$= 0.12], "free" [F (4, 116) = 3.19, P = 0.02, $\eta\rho^2$= 0.10], and "bored" [F (4, 116) = 3.57, P = 0.01, $\eta\rho^2$= 0.11]. A paired t-test revealed that participants felt slightly less "active" after drinking sample VJB sample on test day as compared to retest day [t (29) = -2.07, P = 0.048], as shown in Figure 3(A). In addition, participants' self-reported rating of the "disgusted" emotion was higher during the test session than the retest session for VJB [t (29) = 3.53, P = 0.001] and VJE [t (29) = 2.52, P = 0.02] samples [Fig. 3(B)]. Participants reported feeling less "free" during a test session than during a retest session [t (29) = -2.26, P = 0.03] in response to the VJD sample [Fig. 3(C)]. As shown in Figure 3(D), participants reported to feeling less "bored" during the test session in response to the VJD [t (29) = -2.19, P = 0.04] sample but more "bored" during the test session in response to the VJE [t (29) = 2.63, P = 0.01] sample compared to retest session. In addition, a RM-ANOVA also revealed significant interaction between session and product for a self-reported "secure" emotion [F (4, 116) = 2.84, P = 0.03, $\eta\rho^2$= 0.09], but this data is not included since post-hoc paired t-tests showed no significant difference between test and retest sessions for any products for self-reported "secure".

With respect to facial expressions and autonomic nervous system responses, there were no significant interactions between session and product for overall liking ($P > 0.05$ for all; for details, see Supplementary Table 3).

The Wilcoxon-Signed rank test revealed no significant differences between test and retest sessions in terms of preference rank sums for any product ($P > 0.05$ for all) (data not shown).

The above results demonstrate that 1) a majority of independent variables, i.e., sensory intensities, self-reported emotions, facial expressions, and ANS responses, measured during test and retest sessions showed neither differences between the two sessions nor interaction between session and test product and 2) a change of context, i.e., movement to a different room during preference testing, had little influence on the result from the preference rank test.

4. Discussion

Our previous research found that a combination of self-reported emotions and facial expression analysis along with sensory attribute perception can better predict overall liking and preference rank with respect to basic taste solutions (Samant et al., 2017). Building on these findings, this study was conducted to extend the application of the proposed method to predicting overall liking and preference rank with respect to commercial vegetable juice products. Results from this study reinforce previous findings, suggesting that regression models using a combination of self-reported emotions and facial expressions along with sensory attribute perception produced better results than did models developed separately using the measures when predicting overall liking of commercial vegetable juices. However, the overall variation explained by these independent variables (i.e., sensory attribute intensities, self-reported emotions, facial expressions, and ANS responses) was low for preference rank.

Among sensory attribute perceptions, intensities of saltiness, sweetness, and overall flavor were found to be positively associated with overall liking, while intensities of bitterness and sourness were negatively associated with overall liking. Similar results were observed for preference rank. Although there is no universal association of sensory attribute intensities and overall liking of food/beverage products, some previous studies have found similar results (Crist et al., 2018; Duffy, Rawal, Park, Brand, Sharafi, & Bolling, 2016). In a study on aqueous bitter solutions, Crist et al. (2018) reported that increasing bitter intensity resulted in lower hedonic liking scores among participants. In another study with berry juice products, Duffy et al. (2016) found that sweetness intensity was positively correlated while bitterness and sourness intensities were negatively correlated with overall liking of juices. Moreover, a stepwise regression analysis, using intensities of sweetness, sourness, saltiness, bitterness and astringency as independent variables, found that sweetness was the only significant predictor of overall juice liking (Duffy et al., 2016). Therefore, results from previous research suggest that, although sensory attribute intensities are important to understand liking toward the product, there might be other factors influencing overall liking of the product. It should be also noted that perceived intensities of specific aroma/flavor attributes among mixed-vegetable juice samples were not rated by consumer participants in the present study. In other words, since intensities of specific aroma or flavor attributes, in comparison to intensities of overall aroma or flavor, might better associate with overall liking of and/or preference toward mixed-vegetable juice products, the prediction levels of sensory attribute intensities on overall liking and/or preference should be carefully interpreted in this study, and further study is needed to validate this assumption.

An association between self-reported emotions and hedonic liking has been strongly demonstrated in previous studies (Ng et al., 2013; Köster & Mojet, 2015; Borgogno, Cardello, Favotto, & Piasentier, 2017; Seo & Pramudya, 2018; Waehrens et al., 2018). Specifically, in a recent study with beef samples, Borgogno et al. (2017) measured emotional responses using EsSense25 and showed that positive emotions (e.g., “active” and “satisfied”) were associated with higher liking of beef, while lower liking was connected to negative emotions (e.g., “disgusted”). Concurrent with previous research, a present study found that positive emotions such as “satisfied” and “happy” were associated with highly liked samples, while negative emotions such as “disgusted” and “bored” were negatively associated with overall liking. Interestingly, “guilty” was found to be positively associated with overall liking. Previous studies suggest that “guilty” could be considered as either positive or negative emotion, depending on context (King & Meiselman, 2010; Spinelli, Masi, Zoboli, Prescott, Monteleone, 2015). In other words, while guilty pleasure is linked to a pleasurable or positive experience with a product, a moral judgment that it would be better not to have a product for some reason (e.g., diet or ethics) corresponds to a negative context of the guilt emotion (Spinelli et al., 2015). Self-reported “guilty” in the present study aligns with the former context.

Vegetable juice samples-evoked emotions were also measured by implicit methods, i.e., FE analysis and ANS response measurements. Implicit emotions measured by FE analysis while visually evaluating the appearance of the samples (APP) or after tasting the samples (PTC) were found to be associated with overall liking (Table 1) or preference rank (Table 2) with respect to vegetable juice samples. These findings add evidence to the notion that facial expressions in response to food or beverage samples can relate to overall liking of the test samples (de Wijk et al., 2012, 2014; Samant et al., 2017). However, it should be noted that facial expressions during the initial stages of drinking a vegetable juice sample were probably missed because participants' face was occluded when the sample was taken into the mouth (Samant & Seo, 2018). Because initial impressions toward stimuli influence overall liking of food or beverage samples (de Wijk et al., 2014; Delarue & Blumenthal, 2015) and changes in facial expression are very brief (de Wijk et al., 2012, 2014), a loss of initial facial expressions during tasting stage should be considered when interpreting the results of this study. It is also interesting to note that lower EVs of "joy" during post-consumption (PTC) were found to relate to higher liked samples (model "C" in Table 1), which was contrary to our expectation. Similarly, interesting but unexpected facial expressions toward food or beverage samples have been also reported in other studies (Zeinstra et al., 2009; de Wijk et al., 2012, 2014; He, Boesveldt, de Graaf, & de Wijk, 2014). For example, in a study conducted by de Wijk et al. (2012), not only "neutral" or "sad"-related facial expressions, but also "happy"-related facial expression were more associated with disliked foods compared to liked foods. In previous studies, de Wijk et al. (2014) and He et al. (2014) reported that while "happy"-related facial expressions were rarely observed in the absence of experimental staff during the measurement, such facial expressions were displayed when there was an experimental staff, suggesting that the happy facial expressions might play a role in social function with the staff. In a similar vein, "joy"-related facial expressions might have been displayed when participants tasted disliked juice samples because an experimental staff was present during the facial expression measurement in this study.

The relationships between ANS responses and overall liking of food/beverage samples are generally not straight-forward due to multiple influential factors such as stimulus modality (e.g., visual, olfactory, or gustatory cues), stimulus valence (e.g., pleasant versus unpleasant), and temporal dynamics (e.g., time-series responses to stimuli) (de Wijk et al., 2012, 2014; Danner et al., 2014; He et al., 2014). For example, while unpleasant fish odor instantaneously increased heart rates, pleasant orange odor showed little change in heart rates (He et al., 2014). In addition, because of such dynamic patterns of ANS responses to stimuli, there has been a lack of consistent association between ANS responses and emotions (also see Kreibig, 2000), limiting their use in understanding consumer acceptance of food/beverage samples (Leterme, Brun, Dittmar, & Robin, 2008; Beyts, Chaya, Dehrmann, James, Smart, & Hort, 2017; Samant & Seo, 2018). ANS responses (HR, SCR, and FT) measured in this study, as a physiological manifestation of emotional responses, showed no significant relationships with overall liking of vegetable juice samples. However, higher SCR measured while participants sniffed the samples [i.e., SCR (AR)] was associated with highly-preferred samples (Table 5). Therefore, ANS measures such as phasic EDA (skin conductance response) could be useful in better understanding of preference for vegetable juices among consumers.

Optimum models to predict overall liking (Table 3) and preference (Table 4) were developed by comparing different combinations of predictors, including sensory attribute intensities and emotional responses. Among the prediction models, a model using both sensory attribute intensities and EsSense25 (model “E” in Table 3) as predictors was found to have high R^2_{adj}, low RMSE, low C_p (close to p), and low AICc and BIC values. Addition of FE analysis to this model resulted in a considerable increase in R^2_{adj}, decreasing RMSE, AICc, and BIC values (model "K" in Table 3). This model could be considered as optimum since it provided the balance between positive and negative emotions important to holistic understanding of consumer behavior. However, addition of ANS response as predictors resulted in no advantage (model "O" in Table 3). For preference rank, the optimum model was found to be model "M" in Table 4 based on sensory attribute intensities, FE, and ANS responses, due to its minimization of –*log-likelihood*, AICc, and BIC values. However, it should be noted that R^2 values of prediction models developed for preference rank was low (i.e., $R^2 = 0.04$), suggesting that 4% variation of only on preference rank was explained using attribute intensities, facial expressions, and ANS responses. A reason for a lower R^2 could be that participants' preference rank decision was not completely matched with their overall liking rating. Specifically, Spearman's correlation revealed a significant but moderate correlation between overall liking and preference rank (*rho* = -0.35, $P < 0.001$). Here, negative correlation suggests that higher liked samples were more preferred (1: most preferred; 5: least preferred). In addition, intensity and emotional responses were measured during the same session when participants rated their overall liking, but not when they ranked the samples according to their preference. Therefore, R^2 of prediction models developed for preference rank could be improved if emotional responses are measured while participants perform the preference rank task. Moreover, it is possible that, rather than asking participants to rank the samples, asking them only to choose their most favorite sample could improve the variation explained by the prediction models. These objectives, however, were beyond the scope of the present study.

The present study also investigated test-retest comparisons of overall liking, preference rank, sensory attribute intensities, self-reported emotions, facial expressions, and autonomic nervous system responses. Earlier studies had shown that participants' likings and preferences are not consistent over time (Kremer, Shimojo, Holthuysen, Köster, & Mojet, 2013; Köster, Couronne, Léon, Lévy, & Marcelino, 2003). In other words, initial hedonic ratings measured during sensory testing might not provide reproducible results (Köster et al., 2003). Contrary to those previous findings, this study showed reasonable consistency in term of overall liking and preference rank among participants over a period of two weeks. In addition, sensory attribute intensities were found be consistent over time, with the exception of surface-color intensity. In addition, self-reported emotions, such as "active", "disgusted", "free", and "secure" differed with session for selected samples. For example, participants felt less disgusted with respect to two out of five samples during the retest session compared to for the test session. Although self-reported emotions did not differ between test and retest sessions, a few emotion terms such as "disgusted" showed a significant interaction between session and product (Fig. 3). This result might be due to that participants did not feel as disgusted toward a particular sample in the retest session as they had during the test session. However, in general, self-reported emotions in the present study were quite stable over time. Our findings also showed that individuals' facial expressions and ANS responses to the five vegetable juice samples had no significant interactions between session and product.

5. Conclusion

In summary, results from this study provide empirical evidence that a regression model using a combination of self-reported emotions and facial expressions, along with sensory attribute intensities, better predict overall liking toward commercial vegetable juices than did models separately using the individual measures. While this mirrors the prediction model developed for overall liking of basic taste solutions in a previous study by Samant et al. (2017), unlike in that study, this study found a limited association of self-reported emotions with preference rank. A model using a combination of facial expressions and ANS responses along with sensory attribute intensities as independent predictors was found to be optimal for predicting preference ranks of commercial vegetable juices. However, since the overall variation reflected by these predictors was low, further study is needed to improve model predictability and techniques for predicting consumer preference for food/beverage products. Finally, a test-retest comparison revealed that a majority of individual measures (i.e., sensory attribute intensities, self-reported emotions, facial expressions, and ANS responses) exhibited stability over a period of two weeks.

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Conflict of Interest

All authors declare that no conflict of interest exists in the conduct and reporting of this research.

Table 1. A list of multiple linear regression models of overall liking for commercial vegetable juice products

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
A	**Overall Liking**	**SAI**	Bitterness intensity***	-0.33	0.05
			Sweetness intensity***	0.31	0.04
			Sourness intensity***	-0.21	0.05
			Flavor intensity**	0.10	0.04
B	**Overall Liking**	**EQ**	Disgusted***	-0.44	0.04
			Satisfied***	0.28	0.04
			Bored***	-0.15	0.04
			Secure**	-0.13	0.05
			Guilty**	0.10	0.04
			Happy*	0.11	0.04
C	**Overall Liking**	**FE**	EV Sadness (PTC)***	-0.19	0.05
			EV Contempt (PTC)***	0.18	0.05
			EV Surprise (PTC)***	0.17	0.04
			EV Disgust (PTC)*	-0.14	0.05
			EV Joy (PTC)*	-0.13	0.06
			EV Sadness (APP)**	0.12	0.04
			EV Surprise (APP)*	0.09	0.04
D	**Overall Liking**	**ANS**	N/A		

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), self-reported emotions (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).

EV (APP), EV (AR) and EV (PTC) stand for evidence values of specific emotions exhibited during time windows of appearance, aroma, and post-consumption, respectively.

*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Table 2. A list of ordinal logistic regression models of preference rank for commercial vegetable juice products

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter estimate *(β)*	Standard error (SE)
A	**Preference rank**	**SAI**	Saltiness intensity***	0.43	0.08
			Sourness intensity**	-0.28	0.11
			Bitterness intensity*	-0.22	0.11
B	**Preference rank**	**EQ**	Satisfied*	0.19	0.08
C	**Preference rank**	**FE**	EV Contempt (PTC)*	0.16	0.08
D	**Preference rank**	**ANS**	SCR (AR)**	0.21	0.08

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), self-reported emotions (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).

EV Contempt (PTC) stands for evidence values of contempt emotions exhibited during a time window of post-consumption.

*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Table 3. Model comparison parameters for predicting overall liking of commercial vegetable juice products

Model code	Dependent variable	Independent variables	R^2_{adj}	RMSE	*Cp*	*p*	AIC	BIC
A	**Overall liking**	**SAI**	0.35	0.81	3.65	5	1213.24	1238.36
B	**Overall liking**	**EQ**	0.40	0.78	0.76	7	1173.82	1207.24
C	**Overall liking**	**FE**	0.13	0.93	13.17	8	1358.77	1396.34
D	**Overall liking**	**ANS**	0.00	1	-1.34	1	1421.96	1430.37
E	**Overall liking**	**SAI, EQ**	0.57	0.66	12.52	11	1014.52	1064.45
F	**Overall liking**	**SAI, FE**	0.42	0.76	7.99	11	1158.15	1208.09
G	**Overall liking**	**SAI, ANS**	0.35	0.81	2.69	5	1213.24	1238.36
H	**Overall liking**	**EQ, FE**	0.46	0.74	6.94	14	1129.23	1191.45
I	**Overall liking**	**EQ, ANS**	0.41	0.77	-4.72	8	1169.16	1206.72
J	**Overall liking**	**FE, ANS**	0.13	0.93	8.88	8	1358.77	1396.34
K	**Overall liking**	**SAI, EQ, FE**	0.61	0.63	14.52	18	972.29	1050.78
L	**Overall liking**	**SAI, EQ, ANS**	0.57	0.66	9.11	11	1014.52	1064.45
M	**Overall liking**	**SAI, FE, ANS**	0.42	0.76	7.50	11	1158.15	1208.09
N	**Overall liking**	**EQ, FE, ANS**	0.46	0.74	4.29	14	1129.23	1191.45
O	**Overall liking**	**SAI, EQ, FE, ANS**	0.61	0.63	11.52	18	972.29	1050.78

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), self-reported emotions (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).

RMSE, *Cp*, *p*, AICc, and BIC stand for Root Mean Square Error, Mallow's *Cp*, total significant predictors including intercept, corrected Aikaike Inforymation Criterion, and Bayesian Information Criterion, respectively.

Table 4. Model comparison parameters for predicting preference rank with respect to vegetable juice products

Model code	Dependent variable	Independent variables	R^2	*-loglikelihood*	AIC	BIC
A	**Preference rank**	**SAI**	0.03	781.00	1576.24	1605.51
B	**Preference rank**	**EQ**	0.004	801.76	1613.64	1634.59
C	**Preference rank**	**FE**	0.004	801.90	1613.92	1634.87
D	**Preference rank**	**ANS**	0.004	801.34	1612.81	1633.76
E	**Preference rank**	**SAI, EQ**	0.03	781.00	1576.24	1605.51
F	**Preference rank**	**SAI, FE**	0.03	778.34	1572.96	1606.39
G	**Preference rank**	**SAI, ANS**	0.03	777.65	1571.59	1605.01
H	**Preference rank**	**EQ, FE**	0.007	799.41	1610.98	1636.10
I	**Preference rank**	**EQ, ANS**	0.009	797.91	1607.99	1633.11
J	**Preference rank**	**FE, ANS**	0.008	798.62	1609.41	1634.53
K	**Preference rank**	**SAI, EQ, FE**	0.03	778.34	1572.96	1606.39
L	**Preference rank**	**SAI, EQ, ANS**	0.03	777.45	1571.19	1604.62
M	**Preference rank**	**SAI, FE, ANS**	0.04	775.03	1568.42	1605.99
N	**Preference rank**	**EQ, FE, ANS**	0.009	797.91	1607.99	1633.11
O	**Preference rank**	**SAI, EQ, FE, ANS**	0.04	775.03	1568.42	1605.99

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), self-reported emotions (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).
AICc and BIC stand for adjusted corrected Aikaike Information Criterion and Bayesian Information Criterion, respectively

Table 5. Significant predictors and parameter estimates of the optimum prediction models of overall liking (model "K") and preference rank (model "M") toward commercial vegetable juices

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
K	**Overall liking**	**SAI**	Disgusted***	-0.32	0.04
		EQ	Sweetness intensity***	0.24	0.03
		FE	Sourness intensity***	-0.19	0.04
			Satisfied***	0.18	0.04
			Bitterness intensity***	-0.18	0.04
			EV Surprise (PTC)***	0.14	0.03
			Bored***	-0.12	0.03
			Happy**	0.12	0.04
			Flavor intensity***	0.11	0.03
			EV Sadness (PTC)***	-0.11	0.03
			Secure**	-0.11	0.04
			EV Anger (APP)**	-0.09	0.03
			EV Surprise (APP)**	0.09	0.03
			EV Sadness (APP)*	0.07	0.03
			EV Anger (AR) *	0.07	0.03
			Interested*	0.07	0.03
			Saltiness intensity*	0.07	0.03
M	**Preference rank**	**SAI**	Saltiness intensity***	0.44	0.08
		FE	Sourness intensity**	-0.29	0.11
		ANS	Bitterness intensity*	-0.21	0.11
			SCR (AR) *	0.21	0.08
			EV Contempt (PTC)*	0.18	0.08

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), self-reported emotions (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).
EV (APP), EV (AR) and EV (PTC) stand for evidence values of specific emotions exhibited during time windows of appearance, aroma, and post-consumption, respectively.
*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Supplementary Table 1. Mean intensity ratings (± standard deviation) for the 30 sensory attributes of the 5 vegetable juice samples evaluated by 8 trained panelists

	Vegetable juice samples					*P*-value
	VJA	**VJB**	**VJC**	**VJD**	**VJE**	
Appearance characteristics						
Color	11.93 (±0.96)^{a1}	6.78 (±0.90)^{d}	7.56 (±0.68)^{c}	7.94 (±0.94)^{c}	8.66 (±1.06)^{b}	< 0.001
Aroma characteristics						
Celery	2.66 (±1.68)^{a}	2.94 (±1.32)^{a}	2.43 (±1.48)^{a}	2.68 (±1.49)^{a}	3.29 (±1.32)^{a}	0.07
Cooked tomato	3.88 (±1.49)^{b}	4.59 (±1.64)^{a}	4.60 (±0.78)^{a}	4.53 (±1.57)^{ab}	4.68 (±1.52)^{a}	0.01
Overripe tomato	0.63 (±1.20)^{a}	0.19 (±0.75)^{a}	0.08 (±0.30)^{a}	0.19 (±0.75)^{a}	0.19 (±0.75)^{a}	0.08
Raw pepper	3.63 (±2.36)^{a}	0.78 (±1.40)^{b}	3.56 (±1.58)^{a}	0.44 (±1.20)^{b}	0.66 (±1.42)^{b}	< 0.001
Raw tomato	0.00 (±0.00)^{b}	1.31 (±1.65)^{a}	1.43 (±1.95)^{a}	0.72 (±1.37)^{ab}	0.91 (±1.42)^{a}	< 0.001
Vinegar	1.98 (±2.16)^{a}	0.27 (±0.85)^{b}	1.74 (±1.77)^{a}	0.38 (±0.89)^{b}	0.13 (±0.34)^{b}	< 0.001
Basic tastes						
Bitter	3.06 (±1.25)^{a}	2.13 (±1.20)^{bc}	2.51 (±1.15)^{b}	2.53 (±1.28)^{b}	1.73 (±0.79)^{c}	< 0.001
Salty	5.55 (±0.96)^{b}	6.40 (±1.08)^{a}	4.46 (±1.20)^{c}	4.67 (±1.37)^{c}	6.71 (±1.81)^{a}	< 0.001
Sour	4.86 (±1.73)^{ab}	4.54 (±1.66)^{bc}	5.01 (±1.59)^{a}	4.46 (±1.59)^{c}	3.94 (±1.35)^{d}	< 0.001
Sweet	1.64 (±1.47)^{ab}	2.08 (±1.08)^{a}	1.16 (±1.34)^{b}	1.73 (±1.27)^{ab}	2.14 (±1.04)^{a}	0.03
Flavor characteristics						
Celery	3.61(±1.85)^{b}	3.91 (±1.24)^{ab}	2.84 (±1.46)^{c}	3.38 (±1.04)^{bc}	4.33 (±0.93)^{a}	< 0.001
Cooked tomato	5.03 (±1.26)^{c}	6.22 (±0.98)^{a}	5.26 (±1.19)^{c}	5.77 (±1.17)^{b}	6.41 (±1.12)^{a}	< 0.001
Earthy/Dirty	1.83 (±2.16)^{a}	0.94 (±1.70)^{b}	0.69 (±1.53)^{b}	0.97 (±1.76)^{b}	0.73 (±1.58)^{b}	< 0.001
Metallic	2.14 (±2.00)^{a}	1.43 (±2.01)^{b}	1.46 (±1.76)^{b}	1.39 (±1.78)^{b}	1.48 (±1.63)^{ab}	0.02
Onion/garlic	1.68 (±1.55)^{a}	1.79 (±1.62)^{a}	1.69 (±1.51)^{a}	1.49 (±1.64)^{a}	1.81 (±1.65)^{a}	0.07
Overripe tomato	3.09 (±2.71)^{a}	0.70 (±1.51)^{bc}	0.63 (±1.71)^{c}	1.26 (±1.99)^{b}	0.38 (±1.02)^{c}	< 0.001
Raw pepper	4.11 (±2.56)^{a}	1.29 (±2.03)^{b}	3.40 (±2.07)^{c}	1.74 (±2.34)^{b}	1.28 (±1.77)^{b}	< 0.001
Raw tomato	0.74 (±1.41)^{c}	2.14 (±1.72)^{b}	3.74 (±0.92)^{a}	2.04 (±1.83)^{b}	1.33 (±1.67)^{c}	< 0.001

Supplementary Table 1. Mean intensity ratings (± standard deviation) for the 30 sensory attributes of the 5 vegetable juice samples evaluated by 8 trained panelists (continued)

	Vegetable juice samples					*P*-value
	VJA	VJB	VJC	VJD	VJE	
Vinegar	2.59 (±2.13)^{a}	0.83 (±1.35)^{b}	2.97 (±2.34)^{a}	0.85 (±1.55)^{b}	0.86 (±1.42)^{b}	< 0.001
Mouth-feeling characteristics						
Astringent	7.16 (±0.85)^{a}	6.92 (±0.69)^{ab}	7.06 (±0.53)^{a}	7.05 (±0.64)^{a}	6.66 (±0.57)^{b}	< 0.001
Metallic	2.34 (±2.50)^{a}	1.58 (±2.39)^{b}	1.53 (±2.36)^{b}	1.48 (±2.24)^{b}	1.48 (±2.43)^{b}	0.007
Mouthcoating film	3.18 (±1.20)^{a}	3.06 (±0.90)^{ab}	3.05 (±1.12)^{ab}	3.08 (±1.04)^{ab}	2.97 (±1.05)^{b}	0.02
Viscosity	4.35 (±0.80)^{a}	3.93 (±0.62)^{bc}	3.78 (±0.66)^{c}	4.14 (±0.63)^{ab}	3.84 (±0.81)^{bc}	< 0.001
After tastes						
Bitter	1.74 (±1.15)^{a}	1.37 (±0.99)^{a}	1.53 (±1.40)^{a}	1.24 (±0.90)^{a}	0.88 (±0.86)^{a}	0.06
Celery	2.76 (±1.33)^{ab}	2.75 (±1.65)^{ab}	2.07 (±1.59)^{c}	2.24 (±1.50)^{bc}	2.88 (±1.12)^{a}	< 0.001
Cooked tomato	3.23 (±0.86)^{b}	3.94 (±1.15)^{a}	3.58 (±0.86)^{ab}	3.69 (±1.02)^{a}	3.79 (±0.87)^{a}	< 0.001
Earthy/Dirty	0.90 (±1.32)^{a}	0.38 (±1.02)^{b}	0.08 (±0.30)^{bc}	0.19 (±0.75)^{bc}	0.00 (±0.00)^{c}	< 0.001
Metallic	2.92 (±1.99)^{a}	2.29 (±2.26)^{b}	2.04 (±2.24)^{b}	2.26 (±2.25)^{b}	2.03 (±2.28)^{b}	0.001
Onion/garlic	0.88 (±1.44)^{a}	0.84 (±1.39)^{a}	0.75 (±1.34)^{a}	0.85 (±1.39)^{a}	0.75 (±1.34)^{a}	0.11

All samples were evaluated by 8 trained panelists with respect to 30 sensory attributes on scales ranging from 0 to 15 with 0.1 increments.

[1]Mean ratings with different superscripts within each row represent a significant difference at $P < 0.05$.

Supplementary Table 2. Mean intensity ratings (± standard deviation) for the 8 sensory attributes of the 5 vegetable juice samples evaluated by 100 untrained panelists.

	VJA	VJB	VJC	VJD	VJE	*p*-value
Color intensity	11.94 (±2.23)[a][1]	7.22 (±2.56)[d]	7.95 (±2.56)[cd]	8.65 (±2.35)[bc]	9.06 (±2.17)[b]	< 0.001
Overall aroma intensity	10.26 (±2.68)[a]	7.60 (±2.47)[bc]	6.65 (±3.00)[c]	7.48 (±2.81)[bc]	7.79 (±2.56)[b]	< 0.001
Overall flavor intensity	11.38 (±2.15)[a]	9.41 (±2.27)[b]	7.74 (±3.51)[c]	8.04 (±2.94)[c]	9.38 (±2.16)[b]	< 0.001
Sweetness intensity	5.82 (±3.70)[ab]	6.80 (±3.05)[a]	5.12 (±3.67)[b]	5.31 (±2.77)[b]	6.64 (±3.21)[a]	< 0.001
Sourness intensity	8.33 (±3.30)[a]	6.28 (±3.51)[b]	7.96 (±3.51)[a]	5.92 (±3.20)[b]	5.27 (±3.19)[b]	< 0.001
Bitterness intensity	7.70 (±3.62)[a]	5.17 (±3.41)[c]	7.06 (±3.76)[ab]	5.76 (±3.47)[bc]	5.03 (±3.53)[c]	< 0.001
Saltiness intensity	7.23 (±3.17)[a]	7.83 (±3.08)[a]	4.38 (±3.00)[b]	4.73 (±2.82)[b]	7.55 (±2.69)[a]	< 0.001
Viscosity intensity	8.74 (±3.30)[a]	6.68 (±3.18)[bc]	5.43 (±3.12)[c]	6.84 (±2.84)[b]	7.17 (±2.89)[b]	< 0.001

All 5 samples were evaluated with respect to 8 sensory attributes on 15-cm line scales ranging from 0 (extremely light/extremely weak/not at all viscous) to 15 (extremely dark/extremely strong/extremely viscous) by 100 untrained panelists.
[1]Mean ratings with different superscripts within each row represent a significant difference at $P < 0.05$.

Supplementary Table 3. Comparisons between “test” and “retest” sessions with respect to independent and dependent variables

Type of measurement	Variables	Session			Product			Session x Product		
		***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$
Hedonic response	Overall liking	3.28	0.08	0.10	17.74	<0.001	0.38	0.59	0.62	0.02
Sensory attribute intensity	Color intensity	5.22	0.03	0.15	25.09	<0.001	0.46	2.79	0.03	0.09
Sensory attribute intensity	Aroma intensity	1.34	0.26	0.04	14.47	<0.001	0.33	1.01	0.41	0.03
Sensory attribute intensity	Flavor intensity	0.85	0.36	0.03	18.75	<0.001	0.39	0.32	0.86	0.01
Sensory attribute intensity	Sweetness intensity	1.85	0.18	0.06	3.61	0.02	0.11	1.47	0.23	0.05
Sensory attribute intensity	Sourness intensity	1.15	0.29	0.04	7.14	<0.001	0.20	1.41	0.24	0.05
Sensory attribute intensity	Bitterness intensity	0.04	0.84	0.001	5.04	0.001	0.15	2.02	0.10	0.07
Sensory attribute intensity	Saltiness intensity	1.57	0.22	0.05	13.34	<0.001	0.32	0.39	0.81	0.01
Sensory attribute intensity	Viscosity intensity	0.07	0.79	0.002	6.01	<0.001	0.17	0.96	0.43	0.03
Emotion questionnaire	Active	0.002	0.96	0.00	4.34	0.003	0.13	2.63	0.04	0.08
Emotion questionnaire	Adventurous	0.20	0.66	0.01	4.06	0.004	0.12	0.88	0.48	0.03
Emotion questionnaire	Aggressive	0.16	0.69	0.01	1.35	0.26	0.04	0.33	0.74	0.01
Emotion questionnaire	Bored	0.03	0.87	0.001	1.05	0.39	0.04	3.57	0.01	0.11
Emotion questionnaire	Calm	0.26	0.62	0.01	1.56	0.19	0.05	0.75	0.52	0.03
Emotion questionnaire	Disgusted	1.47	0.24	0.05	6.91	0.001	0.19	3.83	0.01	0.12
Emotion questionnaire	Enthusiastic	1.64	0.21	0.05	1.22	0.31	0.04	0.71	0.59	0.02
Emotion questionnaire	Free	0.35	0.56	0.01	1.63	0.17	0.05	3.19	0.02	0.10
Emotion questionnaire	Good	0.80	0.38	0.03	1.45	0.22	0.05	0.34	0.85	0.01
Emotion questionnaire	Good-natured	2.87	0.10	0.09	0.80	0.53	0.03	1.57	0.19	0.05
Emotion questionnaire	Guilty	0.10	0.75	0.003	0.75	0.50	0.03	0.36	0.67	0.01

Supplementary Table 3. Comparisons between "test" and "retest" sessions with respect to independent and dependent variables (continued)

Type of measurement	Variables	Session			Product			Session x Product		
		***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$
Emotion questionnaire	Happy	0.75	0.39	0.03	3.10	0.02	0.10	1.49	0.21	0.05
Emotion questionnaire	Interested	0.82	0.37	0.03	2.12	0.08	0.07	1.31	0.27	0.04
Emotion questionnaire	Joyful	0.45	0.51	0.02	1.06	0.38	0.04	0.55	0.70	0.02
Emotion questionnaire	Loving	3.17	0.09	0.10	0.31	0.87	0.01	0.55	0.70	0.02
Emotion questionnaire	Mild	0.01	0.91	0.00	1.68	0.16	0.06	2.04	0.11	0.07
Emotion questionnaire	Nostalgic	2.32	0.14	0.07	1.84	0.14	0.06	0.84	0.50	0.03
Emotion questionnaire	Pleasant	0.005	0.94	0.00	0.65	0.63	0.02	0.84	0.50	0.03
Emotion questionnaire	Satisfied	3.10	0.09	0.10	0.68	0.61	0.02	0.24	0.91	0.01
Emotion questionnaire	Secure	0.001	0.97	0.00	0.41	0.80	0.01	2.84	0.03	0.09
Emotion questionnaire	Tame	0.19	0.67	0.01	1.17	0.32	0.04	1.04	0.39	0.04
Emotion questionnaire	Understanding	0.49	0.49	0.02	0.48	0.71	0.02	1.06	0.37	0.04
Emotion questionnaire	Warm	0.20	0.66	0.01	1.53	0.20	0.05	2.07	0.09	0.07
Emotion questionnaire	Wild	2.69	0.11	0.09	0.55	0.70	0.02	1.76	0.17	0.06
Emotion questionnaire	Worried	0.00	1.0	0.00	0.94	0.43	0.03	0.43	0.73	0.02
FE (appearance)	EV Joy (APP)	0.12	0.73	0.004	1.07	0.38	0.04	0.98	0.42	0.03
FE (appearance)	EV Anger (APP)	3.16	0.09	0.10	0.75	0.56	0.03	1.21	0.31	0.04
FE (appearance)	EV Surprise (APP)	0.10	0.76	0.003	0.50	0.74	0.02	0.20	0.94	0.01
FE (appearance)	EV Fear (APP)	0.28	0.60	0.01	0.37	0.83	0.01	0.26	0.91	0.01
FE (appearance)	EV Contempt (APP)	0.13	0.72	0.004	0.18	0.95	0.006	1.16	0.33	0.04
FE (appearance)	EV Disgust (APP)	2.23	0.15	0.07	S1.17	0.33	0.04	1.13	0.35	0.04

Supplementary Table 3. Comparisons between "test" and "retest" sessions with respect to independent and dependent variables (continued)

Type of measurement	Variables	Session			Product			Session x Product		
		***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$
FE (appearance)	EV Sadness (APP)	5.28	0.03	0.15	1.54	0.21	0.05	0.26	0.91	0.01
FE (aroma)	EV Joy (AR)	6.56	0.02	0.18	0.92	0.46	0.03	0.63	0.64	0.02
FE (aroma)	EV Anger (AR)	0.18	0.67	0.01	0.31	0.83	0.01	1.03	0.39	0.03
FE (aroma)	EV Surprise (AR)	0.65	0.43	0.02	2.10	0.09	0.07	1.45	0.22	0.05
FE (aroma)	EV Fear (AR)	0.001	0.97	0.00	0.65	0.63	0.02	1.03	0.39	0.03
FE (aroma)	EV Contempt (AR)	5.82	0.02	0.17	0.65	0.63	0.02	1.17	0.33	0.04
FE (aroma)	EV Disgust (AR)	1.78	0.19	0.06	2.97	0.02	0.09	0.21	0.93	0.01
FE (aroma)	EV Sadness (AR)	0.02	0.89	0.001	1.15	0.34	0.04	0.43	0.79	0.02
FE (post consumption)	EV Joy (PTC)	0.01	0.92	0.00	1.08	0.37	0.04	0.31	0.87	0.01
FE (post consumption)	EV Anger (PTC)	0.77	0.39	0.03	1.18	0.32	0.04	0.36	0.84	0.01
FE (post consumption)	EV Surprise (PTC)	0.13	0.73	0.004	2.78	0.03	0.09	0.62	0.65	0.02
FE (post consumption)	EV Fear (PTC)	0.02	0.90	0.001	1.15	0.34	0.04	1.00	0.41	0.03
FE (post consumption)	EV Contempt (PTC)	0.19	0.67	0.01	1.25	0.29	0.04	0.96	0.43	0.03
FE (post consumption)	EV Disgust (PTC)	2.14	0.15	0.07	3.00	0.04	0.09	0.58	0.68	0.02
FE (post consumption)	EV Sadness (PTC)	5.10	0.03	0.15	2.11	0.08	0.07	0.70	0.59	0.02
ANS (appearance)	Heart Rate (APP)	37.23	<0.001	0.56	1.62	0.18	0.05	0.25	0.91	0.01
ANS (appearance)	Skin temperature (APP)	7.74	0.01	0.21	0.11	0.95	0.004	0.90	0.46	0.03
ANS (appearance)	Phasic SCR (APP)	0.53	0.47	0.02	1.63	0.17	0.05	1.87	0.14	0.06
ANS (aroma)	Heart Rate (AR)	10.10	0.004	0.26	0.98	0.42	0.03	1.17	0.33	0.04
ANS (aroma)	Skin temperature (AR)	2.01	0.17	0.07	2.04	0.12	0.07	1.44	0.24	0.05

Supplementary Table 3. Comparisons between “test” and “retest” sessions with respect to independent and dependent variables (continued)

Type of measurement	Variables	Session			Product			Session x Product		
		***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$	***F*-value**	***P*-value**	$\eta\rho^2$
ANS (aroma)	Phasic SCR (AR)	0.97	0.33	0.03	0.27	0.86	0.01	0.29	0.88	0.01
ANS (post consumption)	Heart Rate (PTC)	7.49	0.01	0.21	1.20	0.31	0.04	2.03	0.10	0.07
ANS (post consumption)	Skin temperature (PTC)	0.04	0.84	0.001	0.54	0.62	0.02	0.85	0.45	0.03
ANS (post consumption)	Phasic SCR (PTC)	0.32	0.58	0.01	1.28	0.29	0.04	0.57	0.56	0.02

FE and ANS stand for facial expressions and autonomic nervous system response, respectively.
APP, AR, and PTC indicate a measurement during the time window of appearance, aroma, and post-consumption, respectively.
ηp^2 (partial eta squared) values of 0.01, 0.06, and 0.14 are considered small, medium, and large effect-sizes, respectively (Velasco et al., 2014).
FE and ANS stand for facial expressions and autonomic nervous system response, respectively. APP, AR, and PC indicate a measurement during the time window of appearance, aroma, and post-consumption, respectively. ηp^2 (partial eta squared) values of 0.01, 0.06, and 0.14 are considered small, medium, and large effect-sizes, respectively (Velasco et al., 2014).

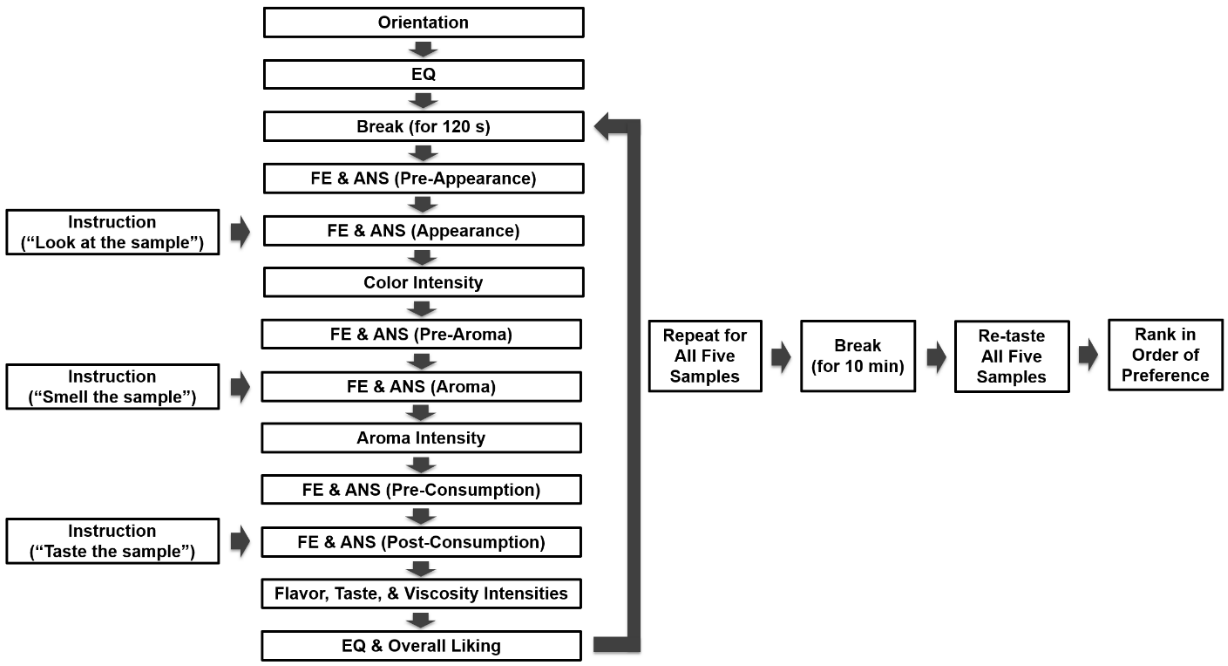


Figure 1. Overall scheme of experimental procedure. FE and ANS stand for facial expression and autonomic nervous system response, respectively.

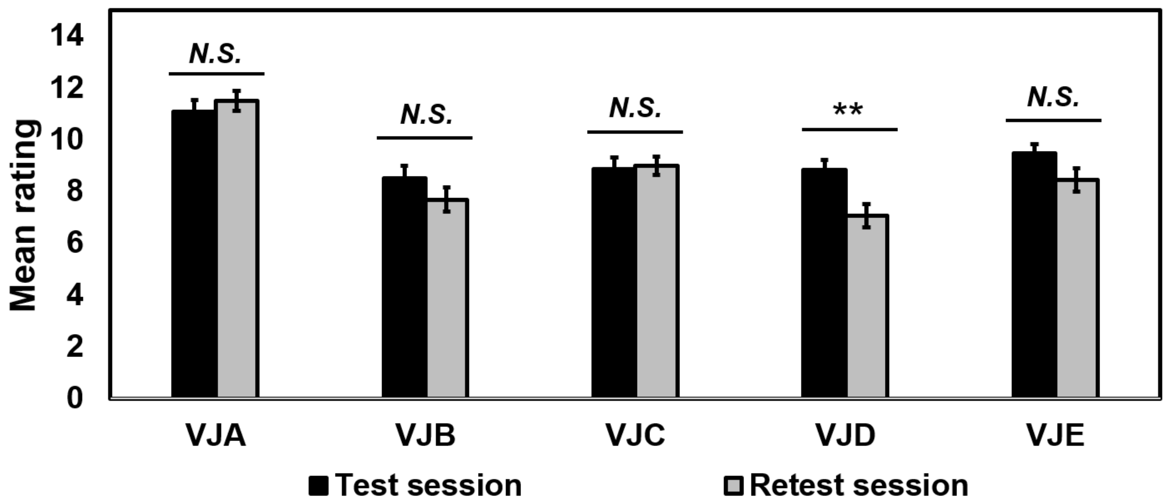


Figure 2. Interaction between "session" and "product" with respect to color intensity among five vegetable juice products. * and ** represent a significant difference at $P < 0.05$ and $P < 0.01$, respectively. *N.S.* represents no significant difference at $P < 0.05$.

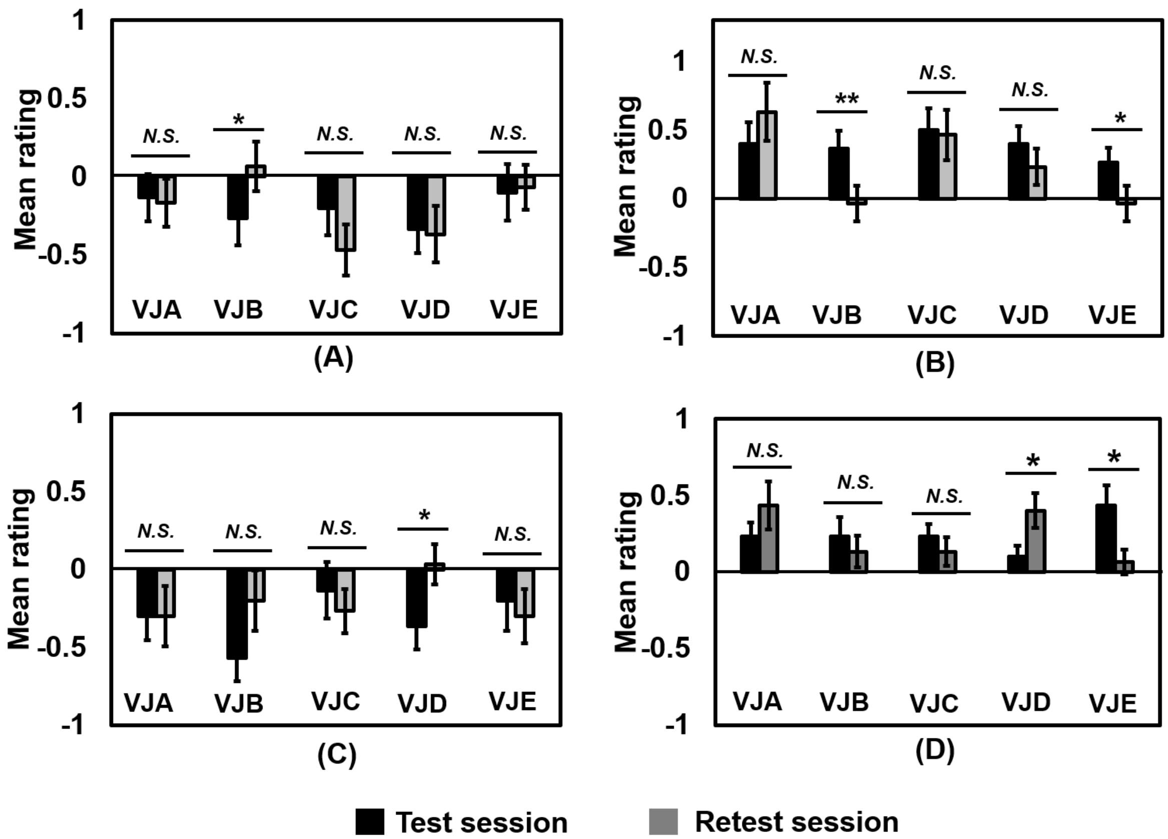
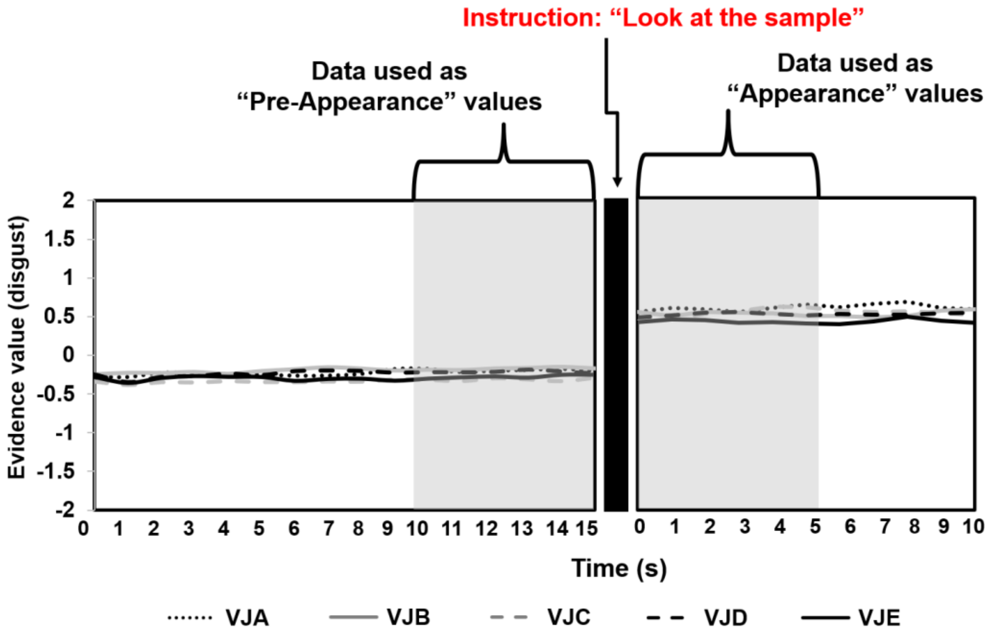
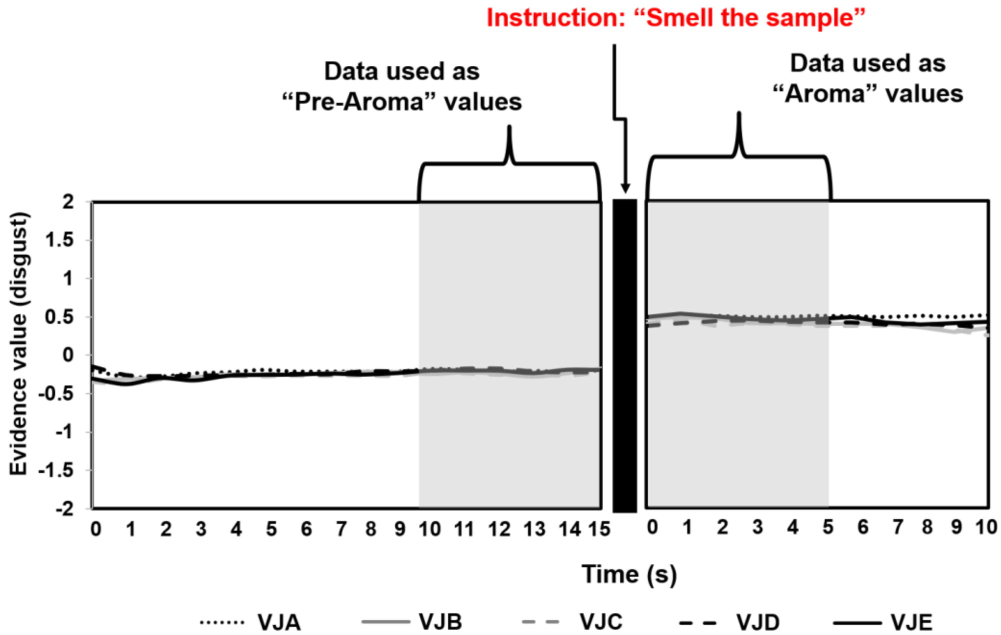


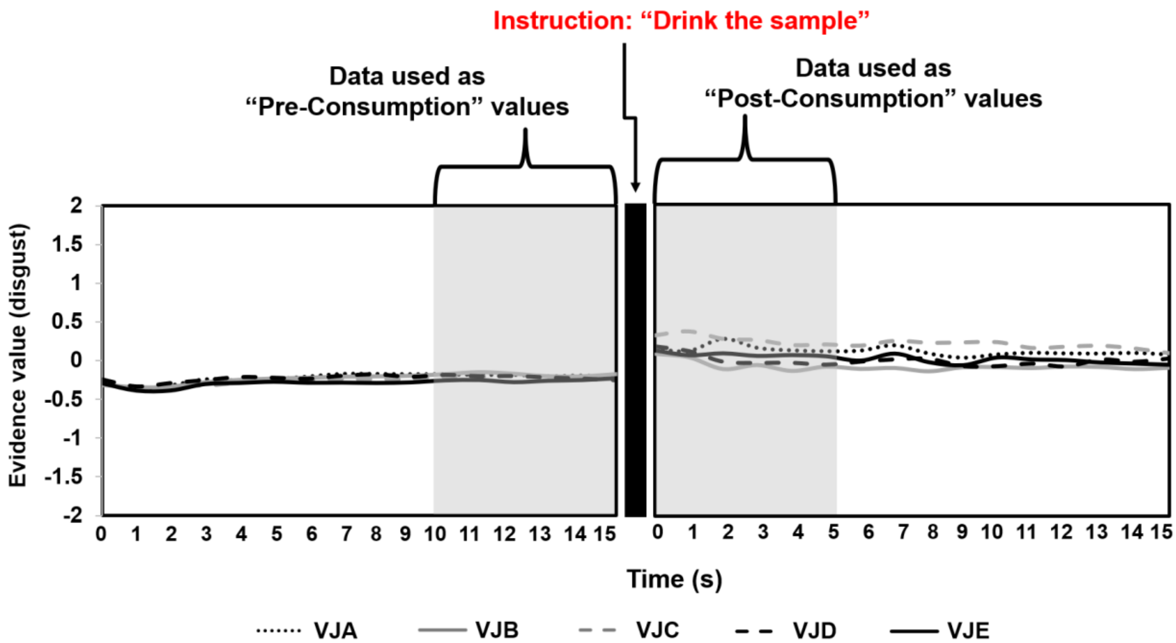
Figure 3. Interactions between "session" and "product" with respect to four self-reported emotional responses toward five vegetable juice products: (A) "active", (B) "disgusted", (C) "free", and (D) "bored". * and ** represent a significant difference at $P < 0.05$ and $P < 0.01$, respectively. *N.S.* represents no significant difference at $P < 0.05$.



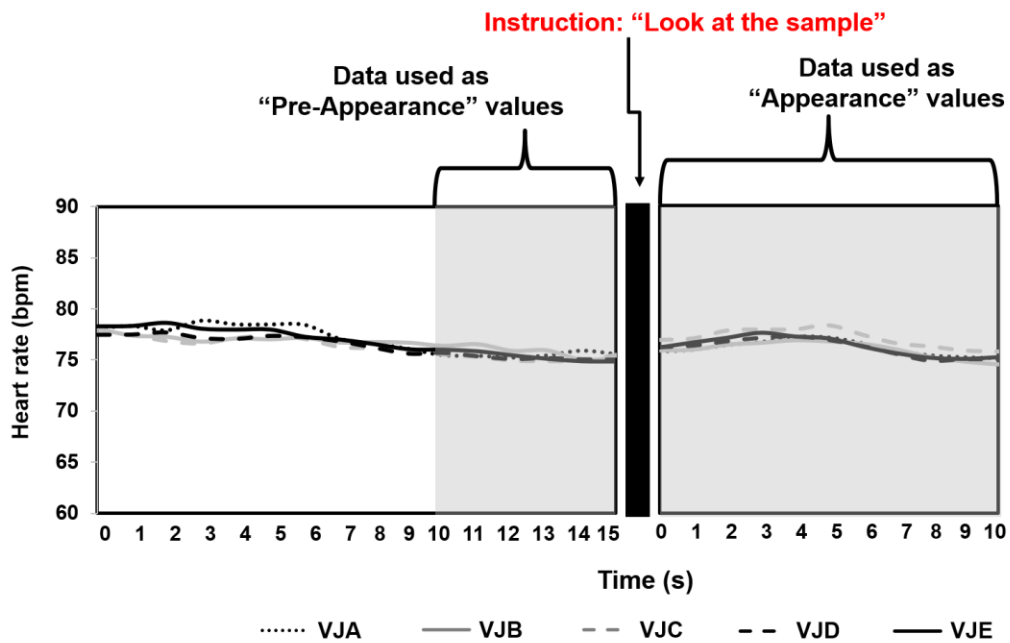
Supplementary Figure 1. Changes in evidence value of “disgust” emotion measured by facial expression analysis over 15 s before (“Pre-Appearance”) and 10 s after (“Appearance”) looking at each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 2. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Aroma") and 10 s after ("Aroma") smelling each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 3. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Consumption") and 15 s after ("Post-Consumption") tasting each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 4. Changes in heart rate value (beats/min) over 15 s before (“Pre-Appearance”) and 10 s after (“Appearance”) looking at each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.

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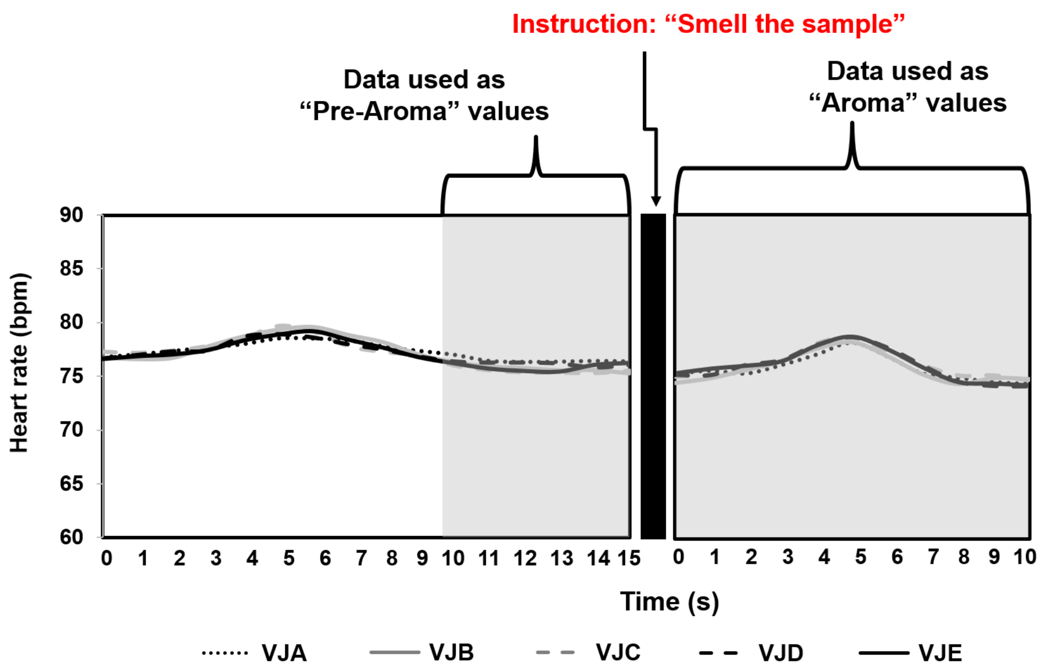
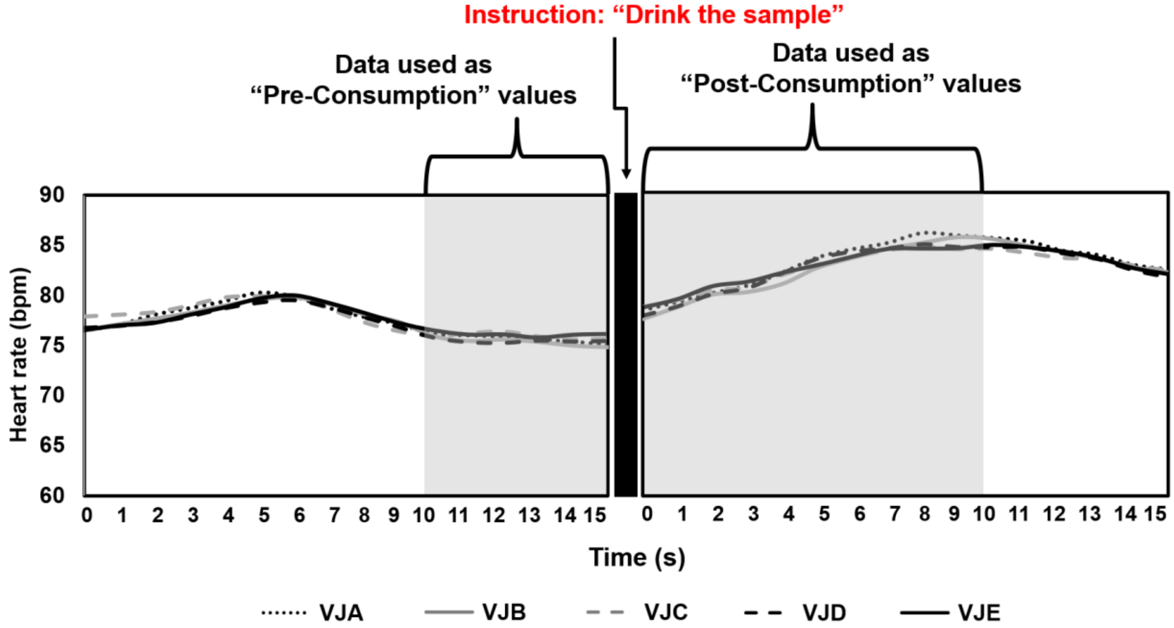


Supplementary Figure 5. Changes in heart rate value (beats/min) over 15 s before (“Pre-Aroma”) and 10 s after (“Aroma”) smelling each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 6. Changes in heart rate value (beats/min) over 15 s before ("Pre-Consumption") and 15 s after ("Consumption") tasting each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.

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Objective 5

Predicting purchase behavior toward mixed-vegetable juices using emotional responses, sensory attributes, and non-sensory factors under informed-tasting condition.

Abstract

While product-related sensory and non-sensory cues have been studied in the past to understand purchase behavior among consumers, there is still little research integrating emotional responses with such cues to achieve better prediction of consumer purchase behavior. The objective of this study was to develop optimum models for predicting purchase intent and final choice using sensory attribute intensities (SAI), non-sensory factors (NSF), and emotional responses. Emotional responses were measured using a self-reported emotion questionnaire (EQ), facial expression analysis (FE), and autonomic nervous system responses (ANS). Sixty-nine healthy adults (36 females) were asked to view the product label of, look at, smell, and drink five commercially-available vegetable juice samples. For each sample, SAI, NSF, EQ, FE, ANS, and purchase intent ratings were measured. After a break, participants were asked to re-visit each sample and select the one sample they would be most likely to buy (final choice). Multiple linear regression revealed that a combination of SAI, NSF, EQ, and FE was best in predicting purchase intent among participants, while ANS measures made only a limited contribution. Logistic regression also revealed that a combination of SAI, NSF, FE, and ANS provided the optimum model for predicting final choices among participants. In conclusion, our findings suggest that a combination of emotional responses, along with sensory and non-sensory factors, is more effective in predicting consumers' purchase behavior when compared to individual measures.

Keywords: Purchase behavior; Emotional responses; Sensory attributes; Non-sensory factor; Facial expression; Vegetable juice

1. Introduction

Both sensory and non-sensory factors affect purchase behavior toward food/beverage products (Danner, Johnson, Ristic, Meiselman, Bastian, 2017; Wardy, Chonpracha, Chokumnoyporn, Sriwattana, Prinyawiwatkul, & Jirangrat, 2018). In other words, when considering purchase and/or repurchase intent of food and beverage items, non-sensory factors such as packaging information play an important role in addition to sensorial acceptability (Cranage, Conklin, & Lambert, 2005; Kytö, Järveläinenb, & Mustonen, 2017). For example, Cranage et al. (2005) showed that providing nutritional quality information about food products resulted in higher repurchasing intent among participants in contrast to when no such information was provided. Kytö et al. (2017) showed that prediction of purchase behavior was lower when participants were not provided with packaging information, when compared to informed-tasting condition, i.e., when participants were provided with packaging information.

Previous research suggests that emotional responses toward food/beverage products are also associated with purchase behavior (Songa, Slabbinck, Vermeir, & Russo, 2019; Spinelli, Masi, Zoboli, Prescott, & Monteleone, 2015). For example, Songa et al. (2019) investigated the association of purchase intent with emotional reactions toward sustainable logos. Findings from the study showed that emotional responses toward packaging labels lead to better understanding of consumers' attitude toward sustainability labels, thereby influencing purchase behavior of the food products. In addition, Spinelli et al. (2015) suggest that emotional responses toward food or beverage products provide crucial information under both blind and informed-tasting conditions.

Measuring food/beverage evoked emotions, characterized as "brief but intense physiological and/or mental reaction to food/beverage-related stimulus" (King & Meiselman, 2010; Kenney & Adhikari, 2016), remains a challenge among researchers. The most popular and convenient method to measure emotional responses is using self-reported questionnaires. These questionnaires are generally composed of either verbal or non-verbal emotion terms (King & Meiselman, 2010; Spinelli & Niedziela, 2016; Swaney-Stueve, Jepsen, & Deubler, 2018). Another method to measure emotional responses is facial expression (FE) analysis. Computer software are available with built-in information about changes in facial expressions in response to different emotions (iMotions, 2017; Tian, Kanade, & Cohn, 2005). A third approach to measure emotional response is to measure physiological changes in the human body as a reaction to emotional experience generally using autonomic nervous system (ANS) response analysis. These changes can mainly be observed in electro dermal activity (EDA) of the skin measured as skin conductance response (SCR), cardiovascular activity measured as heart rate (HR), and skin temperature (ST) (Kenney & Adhikari, 2016; Samant & Seo, 2018a).

Advantages and disadvantages of the above-mentioned methods to measure food-evoked emotional response have been reviewed by multiple researcher groups (Kaneko, Toet, Brouwer, Kallen, and van Erp, 2018; Kreibig, 2010; Lagast, Gellynck, Schouteten, De Herdt, & De Steur, 2017; Spinelli & Niedziela, 2016). More specifically, using self-reported emotions could lead to information loss if participants are not able to correctly translate their experience to expression (Lagast et al., 2017). While FE and ANS methods might have an advantage in this case since they measure involuntary reactions to emotional expression (Kreibig, 2010), these methods are more complex to execute compared to self-reported questionnaires. However, while self-reported questionnaires are more explicit and measure more number of positive emotions, facial expressions are more implicit and measure more number of negative emotions (Lagast et al., 2017; Zeinstra, Koelen, Colindres, Kok, & de Graaf, 2009). Considering such advantages and disadvantages, Samant, Chapko, and Seo (2017) investigated the use of combination of techniques for measuring food/beverage-evoked emotions, in addition to sensory attribute perception, to develop prediction models of consumer liking and preference toward basic taste solutions. The results from that study showed that a combination of self-reported ratings and facial expression analysis, along with sensory attribute intensities, can better predict acceptance and preference toward basic taste solutions when compared to individual variables. Extending these prediction models to commercially-available products, our lab conducted another study exploring the above-mentioned prediction models for commercially-available vegetable juice products (Samant & Seo, 2018b). Results from that study mirror the ones from Samant et al. (2017) wherein optimum model for overall liking comprised of sensory attribute intensities, self-reported emotions, and facial expression analysis. However, the study (Samant & Seo, 2018b) was conducted under blind conditions, i.e., participants were not provided with packaging information about the products they were tasting. Previous research showed that food/beverage evoked-emotions can differ when measured under blind conditions compared to informed conditions (Danner et al., 2017; Gutjar, Dalenberg, de Graaf, de Wijk, Palascha, Renken, & Jager, 2015; Kytö et al., 2017). Gutjar et al. (2015) demonstrated that in addition to consumer acceptance of a food/beverage product, emotional responses measured during informed-tasting conditions provide additional valuable information to understand participants' final food choice. It is, therefore, important to measure emotional responses under informed conditions to holistically understand purchase behavior among consumers.

As described earlier, previous research has shown that sensory factors such as taste intensity as well as non-sensory factors such as brand and product familiarity can influence purchase behavior (Danner et al. 2017; Wardy et al., 2017). However, not much research is available to understand the role of emotions as a predictor of purchase behavior, in addition to sensory and non-sensory factors. Moreover, comparison of individual versus combination of methods to measure emotional responses to predict purchase behavior under informed-tasting conditions has not been fully explored. Therefore, the objective of this study was to develop prediction models to predict purchase behavior under informed-tasting conditions. This is the first study, to the best of the authors' knowledge, aimed at developing prediction models of consumer purchase intent toward commercial vegetable juice products as well as their final purchase choice using a combination of emotional responses, sensory attributes, and non-sensory factors as predictors. Herein, emotional responses were measured using a combination of a self-reported emotion questionnaire, facial expression analysis, and ANS response analysis. In addition, multiple sensory attributes intensities (e.g., color, aroma, flavor, saltiness, sourness, sweetness, bitterness, and viscosity) and non-sensory factors (e.g., product familiarity, brand liking, and frequency of purchase) were measured. Because of their high nutritional aspects and health benefits (Shishir & Chen, 2017), vegetable juice products were chosen as the target product in this study. Because many vegetable-juice products commercially available in a market consist of mixed vegetables, mixed-vegetable juice products were used as test samples in this study.

2. Materials and Methods

The protocol used in this study was approved by the Institutional Review Board of the University of Arkansas (Fayetteville, AR). Experimental procedure was explained and a written consent indicating voluntary participation was obtained from each participant prior to beginning the study.

2.1 Participants

The present study was conducted as a continuation of a previous study that developed optimum prediction models of overall liking for and preference rank toward vegetable juice products under blind-tasting condition using a combination of emotional responses and sensory attribute intensities. A total of 100 participants completed that study [50 females, mean age ± standard deviation (SD) = 41 ± 13 years]. These participants were vegetable juice drinkers and reported to have no known food allergies or clinical histories of major disease. All participants were recruited through the University of Arkansas Sensory Service Center having a database of 6,200 Northwest Arkansas residents. Out of these 100 participants, 69 participants [36 females, mean age ± standard deviation (SD) = 43 ± 13 years] completed the present study. We decided to include only those participants in the present study who had previously completed the blind-tasting session because we were interested to compare blind-tasting versus informed-tasting conditions in terms of all measured variables, results of which are addressed in a different study.

2.2. Sample preparation

Five commercially-available vegetable juice products were used in this study including VJA (365® Everyday Value Organic Juice Vital Veggie, Whole Foods Market, Austin, TX, USA), VJB (Great Value™ Vegetable Juice, Wal-Mart Stores, Inc., Bentonville, AR, USA), VJC (R.W. Knudsen Family Organic Very Veggie® Low Sodium, Knudsen & Sons, Inc., Chico, CA, USA), VJD (V8® Original Low Sodium Juice, Campbell Soup Co., Camden, NJ, USA), and VJE (V8® Original Juice, Campbell Soup Co., Camden, NJ, USA). These five products were chosen as test samples because they showed variations in sensory attributes in the previous study (Samant & Seo, 2018b); more specifically, descriptive sensory analysis found that the five samples differed significantly with respect to 25 sensory attributes (for details, see Samant & Seo, 2018b).

All samples were purchased from local markets in Fayetteville, AR, USA. Each sample was served at refrigerated temperature (approximately, 4 °C) in 60-mL soufflé cups (Pettus Office Products, Little Rock, AR, USA) identified by a 3-digit code.

2.3. Measurement of emotional responses

2.3.1. Self-reported emotion questionnaire (EQ)

A reduced version of the EsSense Profile® (39 items; King & Meiselman, 2010) known as EsSense25 (25 items; Nestrud, Meiselman, King, Lesher, & Cardello, 2016) was used to measure self-reported emotions. Participants rated each item of the EsSense25 on a 5-point scale ranging from 1 (not at all) to 5 (extremely).

2.3.2. Facial expression (FE) analysis

Facial expression software (version 7.0, iMotions, Inc., MA, USA) was used for recording and analyzing seven basic universal expressions of human emotions (i.e., joy, anger, surprise, fear, contempt, disgust, and sadness). Each emotion was measured at a sampling rate of 102.4 Hz and reported as "evidence value" (EV). EVs represent logarithmically (base 10) the odds of an emotion being present in a participant's facial expression when compared to his or her neutral state (iMotions, 2017).

2.3.2. Autonomic nervous system (ANS) response

As in our previous studies (Samant et al., 2017; Samant & Seo, 2018a), ANS responses measured in this study were heart rate (HR; unit: beats/minute), skin temperature (ST; unit: °C), and skin conductance response (SCR; unit: µSiemens). HR and SCR were measured at a sampling rate of 102.4 Hz using a SHIMMER™ sensor (SHIMMER™, Dublin, Ireland), a flexible and non-invasive sensing platform (Burns et al., 2010). HR was measured by placing a Velcro-strap electrode on the proximal phalanges of participant's ring finger, while SCR was measured by placing two electrodes on the proximal phalanges of index and middle fingers of the participant's non-dominant hand. In addition, ST (unit: °C) was measured at every 0.2 s intervals by placing an eSense skin temperature sensor for Android devices (Mindfield® Biosystems Ltd., Gronau, Germany) on the palm of each participant's non-dominant hand.

2.4. Measurements of sensory attribute intensities

Participants rated their perceived color-intensities of test samples on 15-cm line scales ranging from 0 (extremely light) to 15 (extremely dark). They also rated intensities of perceived overall aroma, overall flavor, sweetness, sourness, bitterness, and saltiness on 15-cm line scales ranging from 0 (extremely weak) to 15 (extremely strong). Finally, participants rated perceived viscosity of the samples on 15-cm line scales ranging from 0 (not at all viscous) to 15 (extremely viscous).

2.5. Measurements of overall liking and purchase intent

Levels of overall liking of the samples were measured using traditional 9-point hedonic scales ranging from 1 (dislike extremely) to 9 (like extremely). Participants also provided answer to the question *"how likely are you to purchase this product"* on a 9-point category scale ranging from 1 (extremely unlikely) to 9 (extremely likely).

2.6. Measurements of non-sensory factors

Participants were asked to rate *"How familiar are you with this product?"* on a 9-point category scale ranging from 1 (extremely unfamiliar) to 9 (extremely familiar). Participants also provided answer to the question *"How much do you like this brand of product"* on a 9-point category scale ranging from 1 (dislike extremely) to 9 (like extremely). Finally, participants were asked how often they consumed the product on a 8-point category scale (1 = never, 2 = less than once a month, 3 = 1-3 times a month, 4 = 1-2 times a week, 5 = 3-4 times a week, 6 = 5-6 times a week, 7 = once a day, 8 = 2 or more times a day).

2.7. Procedure

2.7.1 Instruction and experimental set-up

The experimental procedure (whose detailed scheme is illustrated in Figure 1) was carefully explained to each participant prior to starting. Each participant first rated each of 25 emotions on the EsSense25 scale based on how much of each emotion she/he felt at that moment. Facial expressions were measured by a camera (Logitech Europe S.A., Nijmegen, Netherlands) placed in front of the participant while carefully adjusting chair height to ensure a clear view of each participant's face. Next, each participant's non-dominant hand was cleaned using 70% (v/v) isopropanol (PL developments, Clinton, SC, USA) and a conductive electrode cream (Synapse®, Kustomer Kinetics, Inc., Arcadia, CA, USA) gently spread over the proximal phalanges of the index and middle fingers. Electrodes were attached to the non-dominant hand of the participant to measure SCR, HR, and ST, as described above.

2.7.2. Test session

Each participant was asked to evaluate five samples in a randomized sequential monadic fashion. Approximately 45-mL of each sample was presented in a 60-mL soufflé cup. Each participant was instructed to keep her/his hand movement to a minimum and advised against talking during the entire length of the study to avoid noise in the FE and ANS response measures.

Prior to serving each sample, each participant was asked to look at a packaging image, i.e., a picture of the market product label of the vegetable juice product being served to her/him. The price of each product was also displayed below the label image. FE and ANS responses were measured for 15 s before each participant began looking at the packaging label (a "pre-label" time window) and for 15 s while viewing the image (a "label" time window). Each participant was next asked to evaluate sample appearance by looking at the sample. FE and ANS responses were measured for 15 s before the participant began looking at the sample (a "pre-appearance" time window) and for 10 s while he/she visually evaluated appearance of the sample's appearance (an "appearance" time window). The participant then was asked to rate the intensity of color of the sample.

Following appearance evaluation, the participant was asked to evaluate the aroma of the sample by sniffing the sample. FE and ANS responses were measured for 15 s before participants began smelling the sample (a "pre-aroma" time window) and for 10 s while he/she was sniffing it (an "aroma" time window). The participant was then asked to rate the intensity of the sample's aroma.

Finally, the participant was instructed to pour the entire sample into his/her mouth and swallow it while continuously looking at the camera. FE and ANS responses were measured for 15 s before each participant poured the sample into her/his mouth (a "pre-consumption" time window) and for 15 s after she/he had swallowed the sample (a "post-consumption" time window). Each participant also was asked to rate the intensities of overall flavor, sweetness, bitterness, sourness, saltiness, and viscosity, as described in Section 2.4, and also asked to rate each emotion on EsSense25 to measure how the sample made her/him feel. Finally, participants rated their overall liking and purchase intent for each sample, as described in Section 2.5. A two-min break was given between samples.

After tasting all five samples, each participant was given a 10-min break, then asked to view a display of all five sample products together in their original packaging, as commercially available in a market. It should be noted that at this stage the packaging label of each of the products viewed was identical to an image they had previously viewed on a screen. In addition, they were informed of the price of each sample and given the option of re-tasting any of the samples. The purpose of this activity was to reflect informed purchase decision-making situations consumers might experience in real-life scenarios. After careful evaluation, each participant was asked to answer the question "*Which is the one sample you would buy right now if you had to pay using your own money?*", with the answer reported by each participant considered to be his/her final choice. Finally, participants were asked to answer questions related to non-sensory factors such as familiarity toward each product, liking of the brand and frequency of purchase, as described in Section 2.6.

2.8. Data analysis

2.8.1. Self-reported emotions

Evoked-emotions by samples were obtained by subtracting each participant's baseline emotion rating measured prior to beginning the study from rating after consumption of each sample. These subtracted values were used for subsequent statistical analysis.

2.8.2. Facial expression (FE) analysis and autonomic nervous system (ANS) response analysis

Prior to statistical analysis, we examined how FE and ANS responses might have changed in the pre-label, label, pre-appearance, appearance, pre-aroma, aroma, pre-consumption, and post-consumption time windows. For example, heart rate reflected a mostly stable response during the last 5 s in the pre-label, pre-appearance, pre-aroma, and pre-consumption time windows (see supplementary Figures 1 to 4). Since disgust emotion measured by FE followed a similar trend (see supplementary Figures 5 to 8), the last 5 s of pre-label, pre-appearance, pre-aroma, and pre-consumption time windows were selected as “Pre-Label”, “Pre-Appearance”, “Pre-Aroma” and “Pre-Consumption” values, respectively, for FE and ANS responses for each sample.

We next examined label, appearance, aroma, and post-consumption time windows. For the “label” time window, HR and disgust emotion measured by FE over 15 s were considered for further analysis since the participants had viewed the label for the entire time window (supplementary Figures 1 and 5, respectively, and referred to as “Label”). While HR exhibited maximum variation during the first 10 s with respect to appearance, aroma, and post-consumption time windows (supplementary Figures 2 to 4, respectively), the disgust emotion measured by FE exhibited its maximum variation over the first 5 s (supplementary Figures 6 to 8). Since this difference can be attributed to the possibility of ANS response having a slower onset than facial expressions (Danner, Sidorkina, Joechl, & Duerrschmid, 2014), it was decided to use values from the first 10 s of ANS and the first 5 s of FE responses from time windows of label, appearance, aroma and post-consumption (referred to as “Appearance”, “Aroma” and

"Post-Consumption" values) for each sample. Finally, average data obtained by either FE or ANS responses during "Pre-Label", "Pre-Appearance", "Pre-Aroma", and "Pre-Consumption" stage was subtracted from average data exhibited during "Label", "Appearance", "Aroma", and "Post-Consumption" stage, respectively, of each sample, for all participants. These FE values are referred to as FE (LABEL), FE (APP), FE (AR), and FE (PTC), respectively. Similarly, ANS values are referred to as ANS (LABEL), ANS (APP), ANS (AR), and ANS (PTC), respectively.

2.8.3. Statistical analysis

A two-way analysis of variance (ANOVA) was performed using "sample" as a fixed effect and "panelist" as a random effect to compare purchase intent using JMP® Pro (version 14.1, SAS Institute Inc., Cary, NS). If an overall significance was found, a Student's *t*-test was performed for making pair-wise comparisons. In addition, a chi-square test was performed to compare frequency of each sample selected as a "final choice", and if an overall significance was found, pairwise chi-square tests were performed between each sample pair. A statistical difference was defined by $P < 0.05$.

Multiple linear regression analysis using a stepwise platform was used to predict purchase intent of vegetable juice samples. Nominal logistic regression with a backward elimination method using a nominal logistic platform was performed to predict final choice toward vegetable juice samples. In particular, for the nominal logistic regression, if a sample was selected as a final choice, it was labeled as "1", while other samples were labeled as "0". Purchase intent and final selection were used as the dependent variables (fitted separately), while all other variables (i.e., 8 sensory attribute intensities, 3 non-sensory factors, 25 self-reported-emotions on EsSense25, 7 EVs of basic emotions in FE measure, SCR, HR, and ST values in ANS measure) were chosen as independent variables (i.e., predictors). All continuous variables were standardized before use during regression analysis. As described in previous studies (Samant et al., 2017; Samant & Seo, 2018a), for optimum variable selection, a *P*-value stopping criterion used in the multiple linear regression; probabilities for a predictor to enter and leave the model were set at 0.25 and 0.05, respectively. Parameter estimates (β) were reported for each predictor in the model, along with their corresponding standard errors and levels of significance. By definition, in multiple linear regression, β-values represent an estimate of change in a dependent variable that, in turn, corresponds to a unit increase in that independent variable, while all other independent variables are held constant (Klimberg & McCullough, 2013, Chapters 4 and 10). However, in nominal logistic regression, a positive value of β-represents a probability increase in predicting the target category (in this study "1" indicating final choice). Predictors in all models in this study had variable inflation factors (VIF) < 3, indicating low multicollinearity among them (Klimberg & McCullough, 2013, Chapters 4 and 10). Models constructed for purchase intent using a multiple linear regression approach were compared using adjusted R^2 (R^2_{adj}), root mean square error (RMSE), Mallows' C*p*, total number of predictors in the model (p), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC). These parameters have been extensively used in the past for multiple linear regression model comparison (Montgomery Peck, & Vining, 2015, Chapters 3 and 10), and lower values of C*p*, AICc, and BIC are preferred in general (Montgomery et al., 2015). Models constructed for final selection using a nominal logistic regression approach were compared using R^2, *-log-likelihood*, AICc, and BIC. The *-log-likelihood* estimates are often used as model comparison measures for nominal data, with lower values considered to represent better fit (JMP®, 2013). The present study reports models developed using each independent predictor individually, as well as an optimum model developed using a combination of independent variables.

3. Results

3.1. Comparison of purchase intent and final selection between five vegetable juice samples

A two-way ANOVA revealed a significant difference among the five samples in terms of purchase intent [F (4, 272) = 18.10, $P < 0.001$]. As shown in Figure 2, purchase intent ratings of VJC were significantly lower compared to those of VJB ($P < 0.001$), VJD ($P < 0.001$), and VJE ($P < 0.001$), but not VJA ($P = 0.07$). In addition, purchase intent ratings of VJA were significantly lower than those of VJB ($P < 0.001$), VJD ($P < 0.01$), and VJE ($P < 0.001$). The purchase intent ratings of VJE were higher than those of VJD ($P < 0.05$) but not those of VJB ($P = 0.40$). Moreover, no significant difference was found between purchase intent ratings of VJB and VJD ($P = 0.10$). Similarly, frequencies of being selected as a "final choice" differed among the five samples [$\chi^2 = 17.10$, $P < 0.01$] (Figure 3). A frequency of VJC being chosen as a final selection was significantly lower than those of VJA ($P < 0.05$), VJB ($P < 0.001$), VJD ($P < 0.05$), and VJE ($P < 0.01$). VJB also had a higher preference of being selected as the final choice compared to VJD ($P < 0.05$). No significant differences were found among other pairwise sample comparisons ($P > 0.05$, for all).

3.2. Relationships of sensory attribute intensities (SAI) with purchase behavior

As shown in model "PI_A" of Tables 1 and 2, sensory attribute intensities significantly contributed to predict participants' purchase intent and final choice, respectively. Participants exhibited greater likelihood of purchasing vegetable juice samples with higher intensities of sweetness, flavor, and viscosity and lower intensities of bitterness and sourness (model "PI_A" in Table 3). Similarly, model "FC_A" in Table 4 indicates that higher intensities of saltiness and viscosity and lower intensities of sourness were more associated with final product choice.

3.3. Relationships of non-sensory factors (NSF) with purchase behavior

As expected, non-sensory factors contributed significantly to prediction of purchase intent (model "PI_B" in Table 1) and final choice (model "FC_B" in Table 2). Participants were more likely to purchase vegetable juice samples with higher ratings of brand liking and frequency of purchase (model "PI_B" and "FC_B" of Tables 3 and 4, respectively).

3.4. Relationships of emotional responses with behavior

3.4.1. Self-rated emotion questionnaire (EQ)

As shown in model "PI_C" in Table 1, self-reported emotions contributed significantly to prediction of purchase intent. In addition, model "FC_C" in Table 2 shows that self-reported emotions also contribute to prediction of final choices. Positive emotions such as "satisfied" and "nostalgic" exhibited a positive relationship with purchase intent, while negative emotions such as "disgusted" exhibited a negative relationship with purchase intent (model "PI_C" in Table 3).

However, final choice was positively associated only with self-reported “good” emotion (model “FC_C” in Table 4).

3.4.2. Facial expression (FE) analysis

Model “PI_D” in Table 1 shows that facial expressions are significantly associated with purchase intent. As shown in model “PI_D” of Table 3, higher purchase intent was associated with three emotions measured by FE analysis: 1) higher evidence values (EVs) of “surprise” during post-consumption, i.e., EV Surprise (PTC), 2) lower EVs of “disgust” during post-consumption [EV Disgust (PTC)], and 3) lower EVs of “sadness” during post-consumption [EV Sadness (PTC)]. Contribution of FE to prediction of final choice was limited (model “FC_D” in Tables 2 and 4).

3.4.3. ANS response analysis

ANS responses exhibited only limited associations with purchase intent (model “PI_E” in Tables 1 and 3) and final selection (model “FC_E” in Tables 2 and 4).

3.5. Optimal model selection

As shown in Table 5, model “PI_F” developed to predict purchase intent using a combination of sensory attribute intensity (SAI), non-sensory attribute (NSF), self-reported emotions (EQ), and facial expressions (FE) was considered the optimum model for prediction of purchase intent. This model produced the highest R^2_{adj} (0.55), the lowest RMSE (0.67), and the lowest values of AICc (716.18) and BIC (765.04). Sensory attribute intensity serving as significant predictors for this model were: bitterness (β = −0.31, P < 0.001) and overall flavor (β = 0.16, P < 0.001). Significant predictors of non-sensory factors were: brand liking (β = 0.24, P < 0.001) and frequency of purchase (β = 0.14, P < 0.01). In addition, self-reported emotions of "disgusted" (β = −0.15, P < 0.001), "satisfied" (β = 0.18, P < 0.001), "warm" (β = 0.11, P < 0.05), and "understanding" (β = -0.10, P < 0.05) were found to be significant predictors of purchase intent. Based on facial expression analysis, significant predictors were: EV Surprise (PTC) (β = 0.16, P < 0.001), EV Disgust (PTC) (β = -0.17, P < 0.001), and EV Contempt (PTC) (β = -0.10, P < 0.01).

With respect to final choice, model "FC_F" in Table 5, developed using a combination of sensory attribute intensity (SAI), non-sensory factors (NSF), facial expression analysis (FE), and autonomic nervous system responses (ANS), was chosen as an optimum model. This model produced the highest R^2 (0.21), and lower values of *-log-likelihood* (136.15), AICc (286.64), and BIC (313.21). A significant predictor for this model with respect to sensory attribute intensities was saltiness (β = 0.35, P < 0.05). Significant predictors of non-sensory factors were: brand liking (β = 1.21, P < 0.001) and frequency of purchase (β = 0.37, P < 0.05). In terms of facial expressions, EV Contempt (AR) (β = -0.40, P < 0.01) and EV Fear (LABEL) (β = 0.35, P < 0.05) were found to be significant predictors of final choice. Finally, HR (AR) was the only ANS response found to be a significant predictor of final choice (β = 0.34, P < 0.05).

4. Discussion and Conclusion

Samant and Seo (2018b) found that a combination of sensory attribute intensities and emotional responses measured using both explicit and implicit methods better predicted overall liking of mixed vegetable juice products under blind-tasting conditions, i.e., when product-related information was not given to participants. The present study aimed at determining optimum models for predicting purchase behavior when the mixed vegetable juice products are tasted under informed-tasting conditions, i.e., when product-related label information is provided to participants. The findings of this study show that emotional responses provide valuable information, along with sensory and non-sensory factors, for predicting purchase behavior. Specifically, in terms of emotional measures, combination of self-reported emotions and facial expressions worked best in predicting purchase intent. Interestingly, a combination of facial expressions and autonomic nervous system responses, along with sensory and non-sensory cues worked best in predicting final choices.

Numerous research studies have shown that sensory attribute intensities affect purchase intent (Cerrato Rodriguez, Torrico, Osorio, Cardona, & Prinyawiwatkul, 2017). Findings of the present study show that while sensory attribute intensities such as overall flavor, sweetness, and viscosity exhibited positive associations, bitterness and sourness intensities exhibited negative associations with purchase intent. Higher saltiness intensity and viscosity perception, along with lower sourness intensity also contributed to selection of a product as a final purchase choice. These results suggest that while sensory attribute intensities affect both purchase intent rating and final purchase choice, sensory attributes associated with purchase intent rating can be different from those related to final purchase choice. Although there is no universal association of sensory attribute intensities with purchase intent of food/beverage products, similar results have been observed in previous studies (Cerrato Rodriguez, Torrico, Osorio, Cardona, & Prinyawiwatkul, 2017; Crist, Duncan, Arnade, Leitch, O'Keefe, & Gallagher, 2018). For example, Cerrato Rodrigues et al. (2017) found that saltier spreads/emulsions prepared with olive, rice bran, and soya bean oils might be more likely to be purchased. However, it is worth noting that not only sensory perception, but also non-sensory factors might play an important role in influencing purchase-related decisions (Deli-Gray, Haefner, & Rosenbloom, 2011; Enneking, Neumann, & Henneberg, 2007). In a study conducted by Enneking et al. (2007), 621 consumers tasted soft drinks and chose their most preferred products for purchase, and the study showed that preferences were heavily dependent on non-sensory cues, especially brand information. Similarly, Deli-Gray et al. (2011) found that brand familiarity and liking are important predictors of purchase behavior. The present study provides similar results with brand liking and frequency of purchase contributing significantly to prediction of both purchase intent final purchase choice (Table 5).

Previous research lacks clear association between self-reported emotions and purchase behavior (Kytö et al., 2018; Spinelli et al., 2015). For example, Spinelli et al. (2015) measured emotional responses toward hazelnut and cocoa spreads using an *EmoSemio* questionnaire under both blind-tasting and informed-tasting conditions. In that study, self-reported emotions were found to show strong associations with purchase intent, leading to better discrimination among products. However, in another study, Kytö et al. (2017) found that only a minor association existed between emotional responses and purchase behavior. In particular, while binomial regression analysis conducted to predict purchase intent from emotional responses, yielded no significant β-coefficients, self-reported “satisfaction” was found to be the most commonly-selected emotion related to purchase intent (Kytö et al., 2017). The present study showed a significant contribution of self-reported emotions with respect to predicting purchase intent, with “satisfied” emotion showing the strongest association (Tables 1 and 3). However, self-reported emotions made only a limited contribution to predicting final choice, while non-sensory factors such as “brand liking” and “frequency of purchase” provided greater contributions to prediction of final choices (Tables 2 and 4). Further study is also needed to identify factors that induce weak relationship between self-reported emotions and final choices among participants under informed-tasting condition.

Optimum models for predicting purchase intent and final choice were developed by comparing different combinations of predictors, including sensory and non-sensory factors along with emotional responses (Table 5). Model “PI_F” using significant predictors of sensory attributes, non-sensory factors, self-reported emotions, and facial expressions was found to be optimum with respect to predicting purchase intent. With respect to predicting final choice among participants, model “FC_F”, using sensory attributes, non-sensory factors, facial expressions, and autonomic nervous system responses as predictors was found to be optimum. Using a combination of self-reported emotions and physiological measures to help understand consumer behavior toward label information has been demonstrated by Liao, Corsi, Chrysochou, & Lockshi (2015). In their study, self-reported emotions captured emotional information in response to label color, type face, and images on the package, while facial expressions could capture information only in response to images. However, the study focused only on emotional responses toward the packaging elements, not their consequent influence on purchase behavior.

In the present study, facial expression of a “fear” emotion measured in response to viewing of the product label image was found to be positively associated with the product being selected as the final purchase choice (Table 5). This is uncommon, since “fear” is generally considered to be a negative emotion. However, Dunn and Hoegg (2014) provide an explanation for this behavior. According to them, “*since people cope with fear through affiliation with others, in the absence of other individuals, consumers may seek affiliation with an available brand. This, in turn, will enhance emotional attachment to that brand*”. This could be the reason for participants in the present study to express greater fear toward the product label of their most preferred sample for purchase.

To summarize, this study found that a combination of sensory attribute intensities, non-sensory factors (esp., brand liking and frequency of purchase), self-reported emotions, and facial expressions (esp., during post-consumption) can better predict purchase intent of mixed-vegetable juices under informed-tasting condition. In addition, a combination of sensory attribute intensities, non-sensory factors (esp., brand liking and frequency of purchase intent), facial expressions (esp., during smelling and label viewing stages), and autonomic nervous system responses (esp., heart rate during smelling stage) can be effective in predicting final choices of mixed-vegetable juices under informed-tasting condition. In conclusion, our findings suggest that while sensory and non-sensory cues provide predictive information about purchase behavior, emotional responses provide additional important information to those seeking better understanding of purchase intent and final choice toward mixed vegetable juice products when product-related label information is provided to consumers.

Table 1. Model comparison parameters for purchase intent toward commercial vegetable juice samples

Model code	Dependent variable	Independent variables	R^2_{adj}	RMSE	*Cp*	*p*	AIC	BIC
PI_A	**Purchase Intent**	**SAI**	0.31	0.83	6.74	6	861.32	887.89
PI_B	**Purchase Intent**	**NSF**	0.28	0.85	2.04	3	870.03	885.28
PI_C	**Purchase Intent**	**EQ**	0.26	0.86	10.27	5	884.71	907.53
PI_D	**Purchase Intent**	**FE**	0.14	0.93	0.02	4	934.36	953.40
PI_E	**Purchase Intent**	**ANS**	0.00	1	-5.32	1	982.10	989.75

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), non-sensory factors (NSF), self-reported emotion questionnaire (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).

RMSE, *Cp*, *p*, AICc, and BIC stand for Root Mean Square Error, Mallow's *Cp,* total significant predictors including intercept, corrected Aikaike Information Criterion, and Bayesian Information Criterion, respectively.

Table 2. Model comparison parameters for final choice of commercial vegetable juice samples

Model code	Dependent variable	Independent variables	R^2	*-Log-Likelihood*	AIC	BIC
FC_A	**Final choice**	**SAI**	0.06	161.66	331.44	346.70
FC_B	**Final choice**	**NSF**	0.16	145.63	297.33	308.79
FC_C	**Final choice**	**EQ**	0.02	168.79	341.62	349.27
FC_D	**Final choice**	**FE**	0.00	172.64	347.29	351.12
FC_E	**Final choice**	**ANS**	0.00	172.64	347.29	351.12

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), non-sensory factors (NSF), self-reported emotion questionnaire (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).
AICc, and BIC stand for corrected Aikaike Inforymation Criterion, and Bayesian Information Criterion, respectively.

Table 3. A list of multiple linear regression models of purchase intent toward commercial vegetable juice samples

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
PI_A	**Purchase intent**	**SAI**	Bitterness intensity***	-0.39	0.06
			Sweetness intensity***	0.19	0.05
			Flavor intensity**	0.16	0.05
			Sourness intensity*	-0.13	0.06
			Viscosity intensity*	0.11	0.05
PI_B	**Purchase intent**	**NSF**	Brand liking***	0.39	0.05
			Frequency of purchase***	0.23	0.05
PI_C	**Purchase intent**	**EQ**	Satisfied***	0.35	0.06
			Disgusted***	-0.28	0.05
			Understanding*	-0.13	0.05
			Nostalgic*	0.11	0.05
PI_D	**Purchase intent**	**FE**	EV Disgust (PTC)***	-0.33	0.05
			EV Surprise (PTC)***	0.28	0.05
			EV Contempt (PTC)*	-0.11	0.05
PI_E	**Purchase intent**	**ANS**	N/A		

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), non-sensory factors (NSF), self-reported emotion questionnaire (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).
EV (PTC) stand for evidence values of specific emotions exhibited during time window of post-consumption.
*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

Table 4. A list of nominal logistic regression models of final choice of commercial vegetable juice samples

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
FC_A	**Final choice**	**SAI**	Sourness intensity**	-0.50	0.15
			Saltiness intensity*	0.38	0.15
			Viscosity intensity*	0.37	0.15
FC_B	**Final choice**	**NSF**	Brand liking***	1.08	0.26
			Frequency of purchase*	0.34	0.15
FC_C	**Final choice**	**EQ**	Good**	0.40	0.15
FC_D	**Final choice**	**FE**	N/A		
FC_E	**Final choice**	**ANS**	N/A		

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), non-sensory factors (NSF), self-reported emotion questionnaire (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).

*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively

Table 5. Significant predictors and parameter estimate of the optimum prediction models of purchase intent toward and final choice of commercial vegetable juice samples

Model Code	Dependent variable	Independent variables	Significant predictors	Parameter Estimate *(β)*	Standard Error (SE)
PI_F	**Purchase intent**	**SAI**	Bitterness intensity***	-0.31	0.04
		NSF	Brand liking***	0.24	0.04
		EQ	Satisfied***	0.18	0.05
		FE	EV Disgust (PTC)***	-0.17	0.04
			EV Surprise (PTC)***	0.16	0.04
			Flavor intensity***	0.16	0.04
			Disgusted***	-0.15	0.04
			Frequency of purchase**	0.14	0.04
			Warm*	0.11	0.04
			Understanding*	-0.10	0.05
			EV Contempt (PTC)**	-0.10	0.04
FC_F	**Final choice**	**SAI**	Brand liking***	1.21	0.28
		NSF	EV Contempt (AR)**	-0.40	0.15
		FE	Frequency of purchase*	0.37	0.15
		ANS	Saltiness intensity*	0.35	0.16
			EV Fear (LABEL)*	0.35	0.17
			HR (AR)*	0.34	0.16

Prediction models were developed based on independent variables of sensory attribute intensities (SAI), non-sensory factors (NSF), self-reported emotion questionnaire (EQ), facial expressions (FE), and autonomic nervous system responses (ANS).
Optimum Model "PI_F" developed for purchase intent provided highest R^2_{adj} (0.55) and lowest RMSE (0.67), AICc (716.18), and BIC (765.04) values. C_p and p for this model was 23.16 and 12, respectively.
Optimum Model "FC_F" developed for final choice provided highest R^2 (0.21) and lowest *-log-likelihood* (136.15), AICc (286.64), and BIC (313.21).
EV (LABEL) and EV (AR) stand for evidence values of specific emotions exhibited during time windows of viewing product label and aroma, respectively.
*, **, and ***: significant at $P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively.

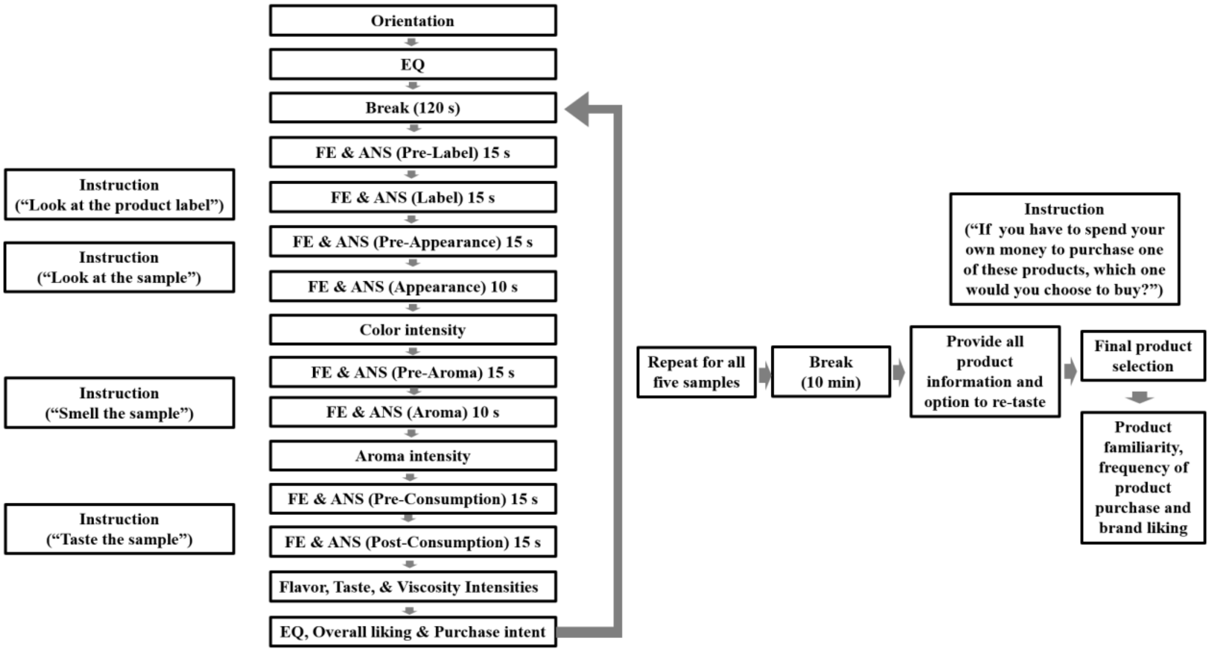


Figure 1. Overall scheme of experimental procedure. EQ, FE, and ANS stand for self-reported emotion questionnaire, facial expression, and autonomic nervous system response, respectively.

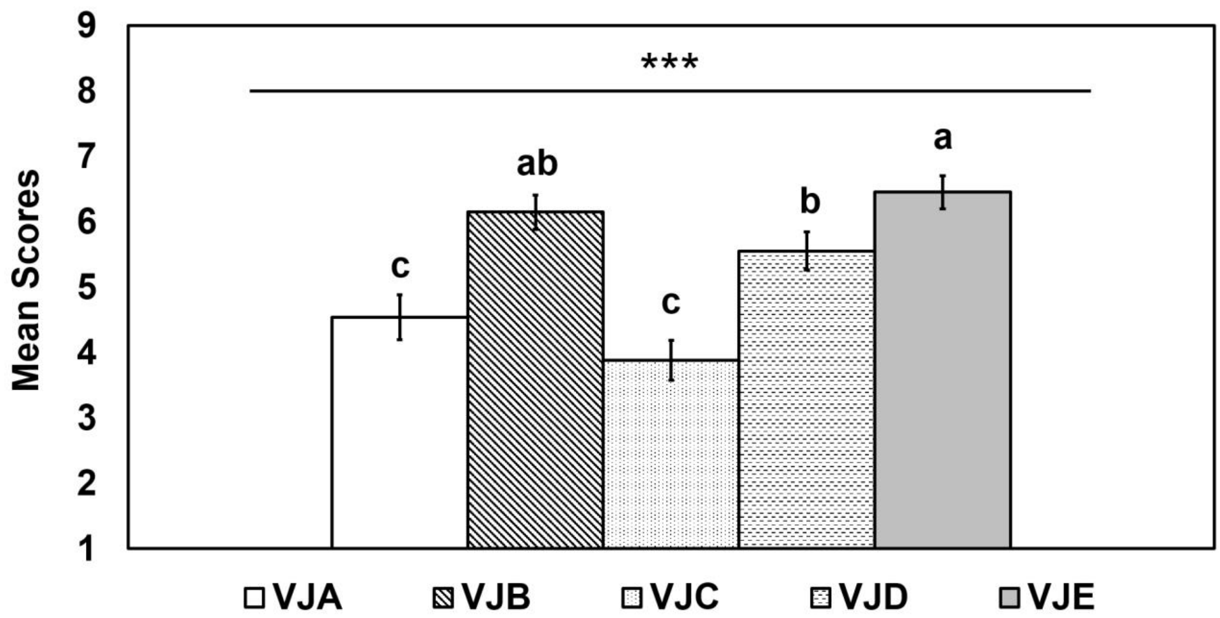


Figure 2. Comparison between five vegetable juice samples with respect to purchase intent. *** represents a significant difference at $P < 0.001$, respectively. Mean ratings with different letters represent a significant difference at $P < 0.05$.

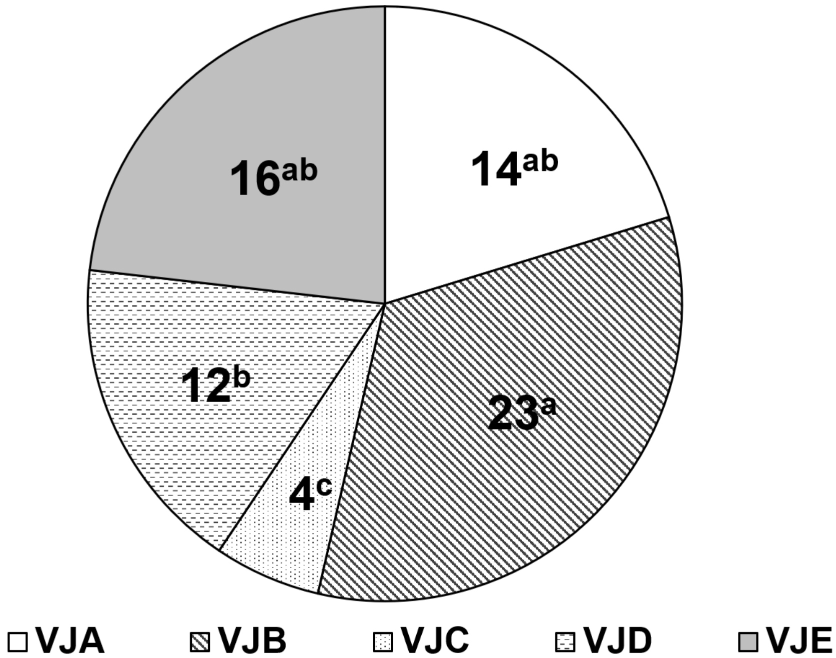
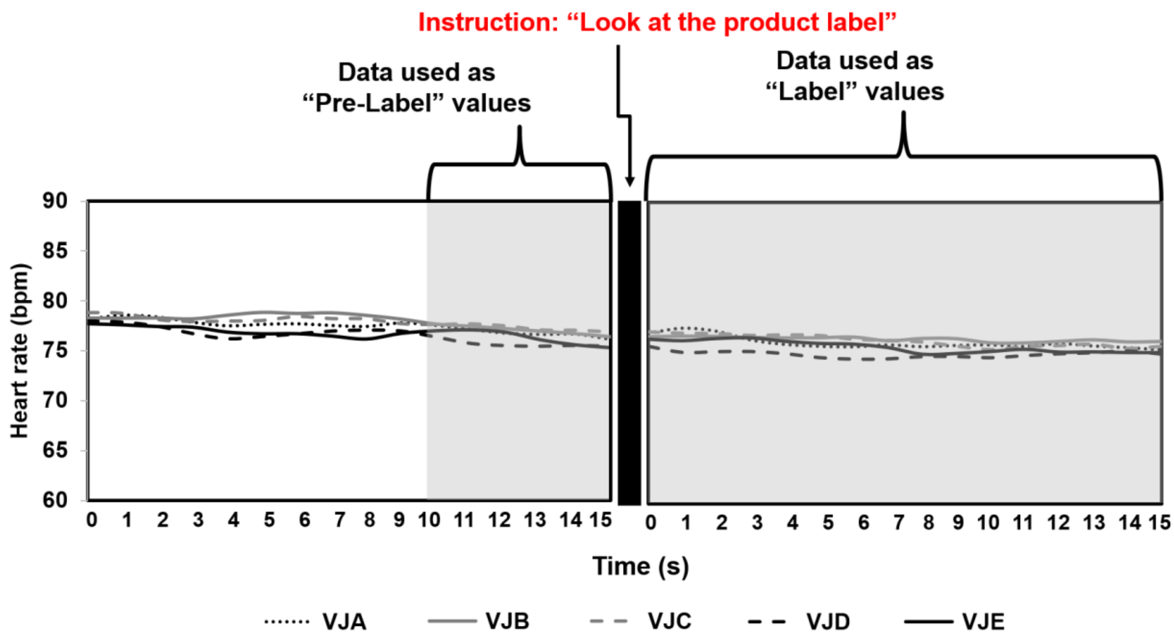
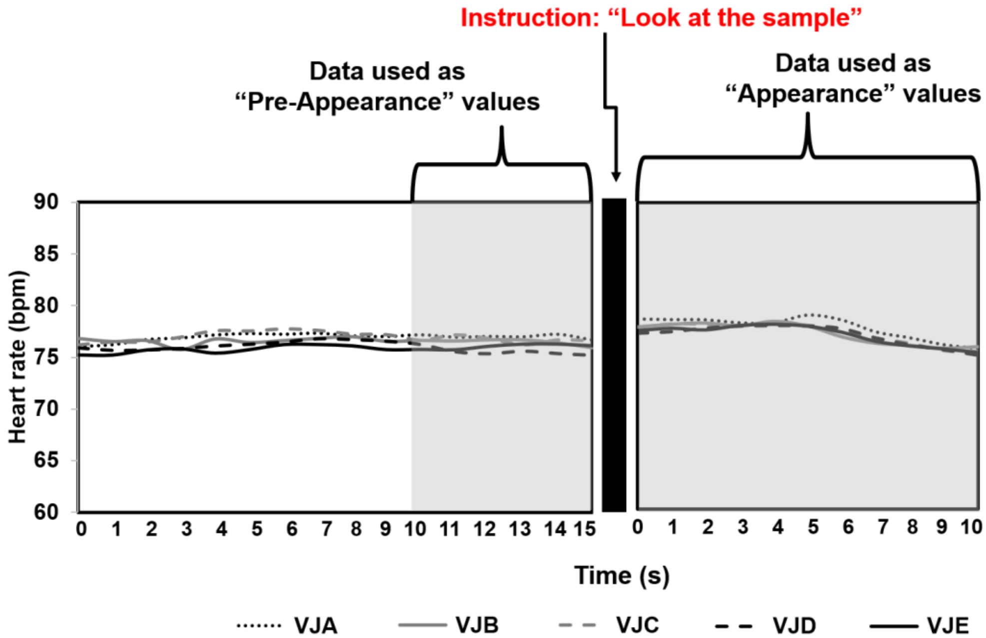


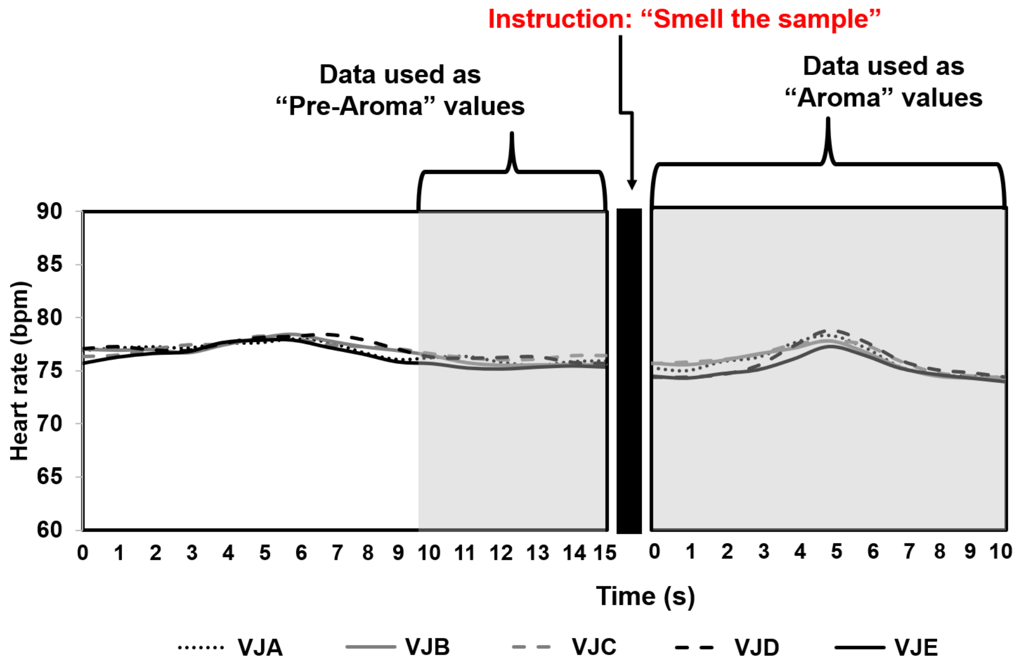
Figure 3. Pie-chart representation of absolute frequency of each vegetable juice sample being chosen as “final choice”. Frequencies with different letters represent a significant difference at $P < 0.05$.



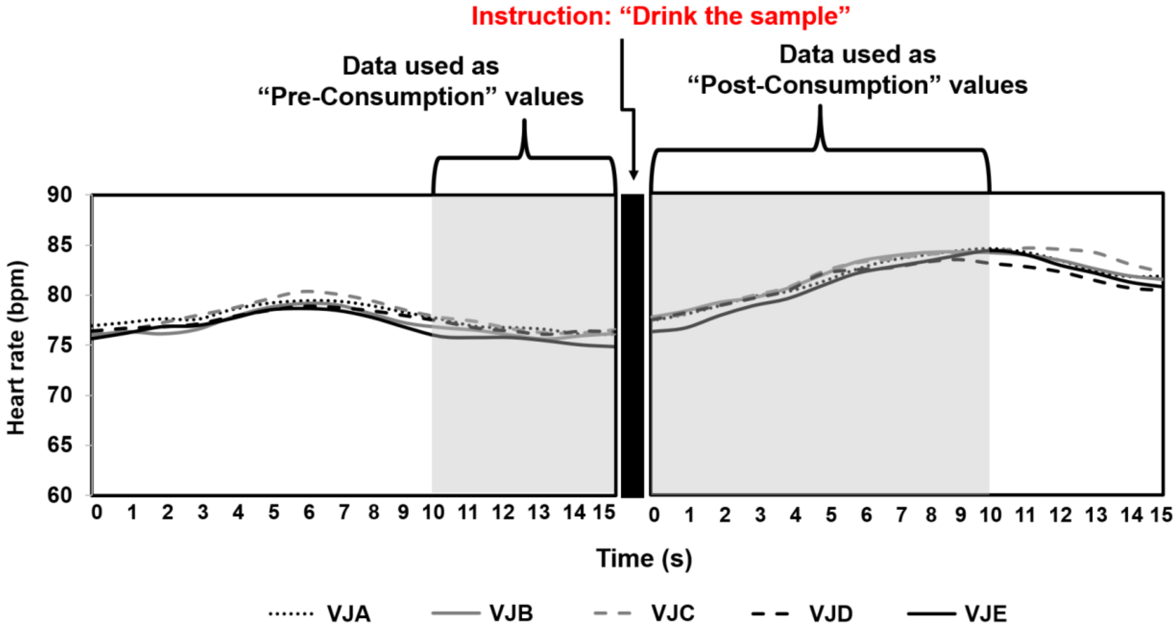
Supplementary Figure 1. Changes in heart rate value (beats/min) over 15 s before ("Pre-Label") and 15 s while ("Label") looking at the product label image of each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



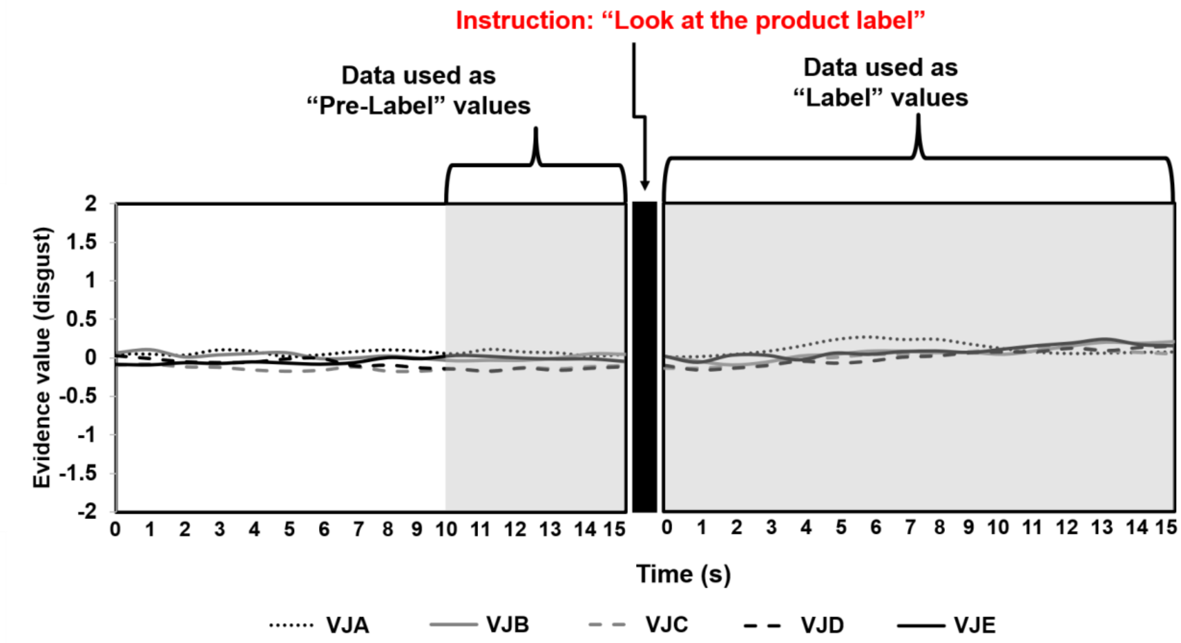
Supplementary Figure 2. Changes in heart rate value (beats/min) over 15 s before ("Pre-Appearance") and 10 s while ("Appearance") looking at each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



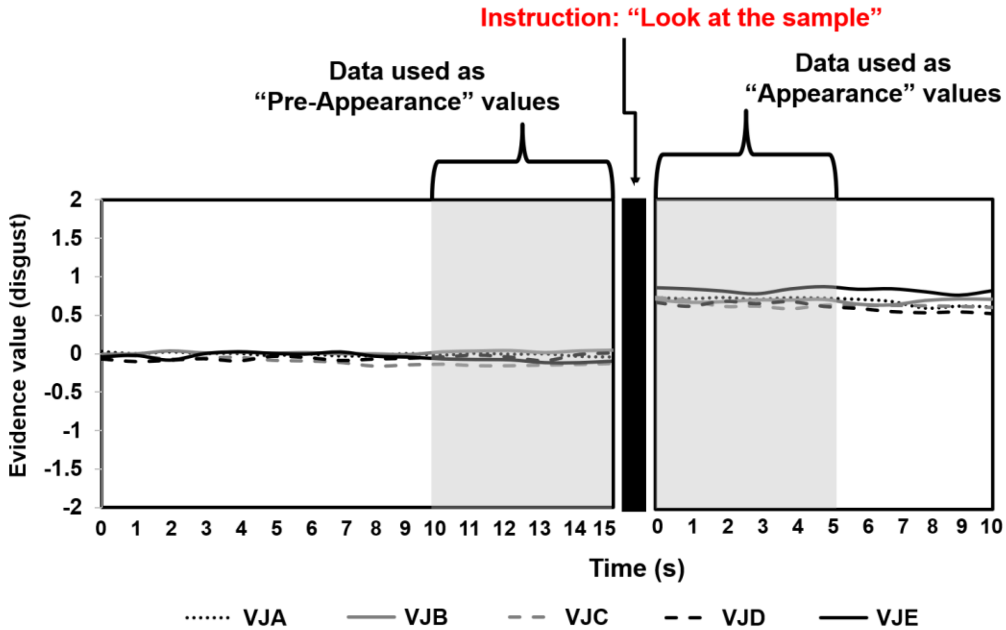
Supplementary Figure 3. Changes in heart rate value (beats/min) over 15 s before (“Pre-Aroma”) and 10 s while (“Aroma”) smelling each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



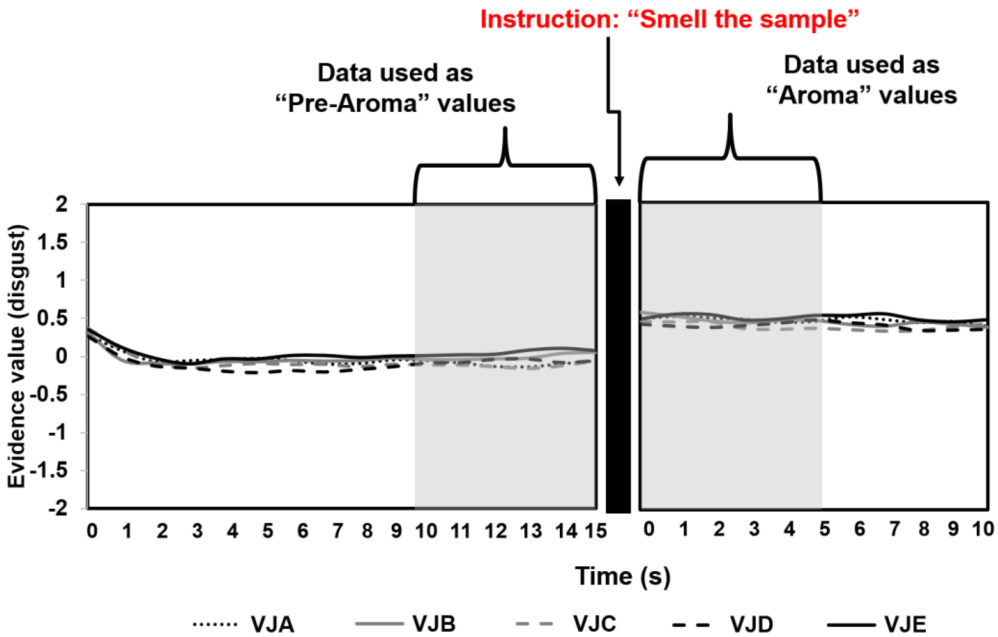
Supplementary Figure 4. Changes in heart rate value (beats/min) over 15 s before ("Pre-Consumption") and 15 s after ("Post-Consumption") tasting each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



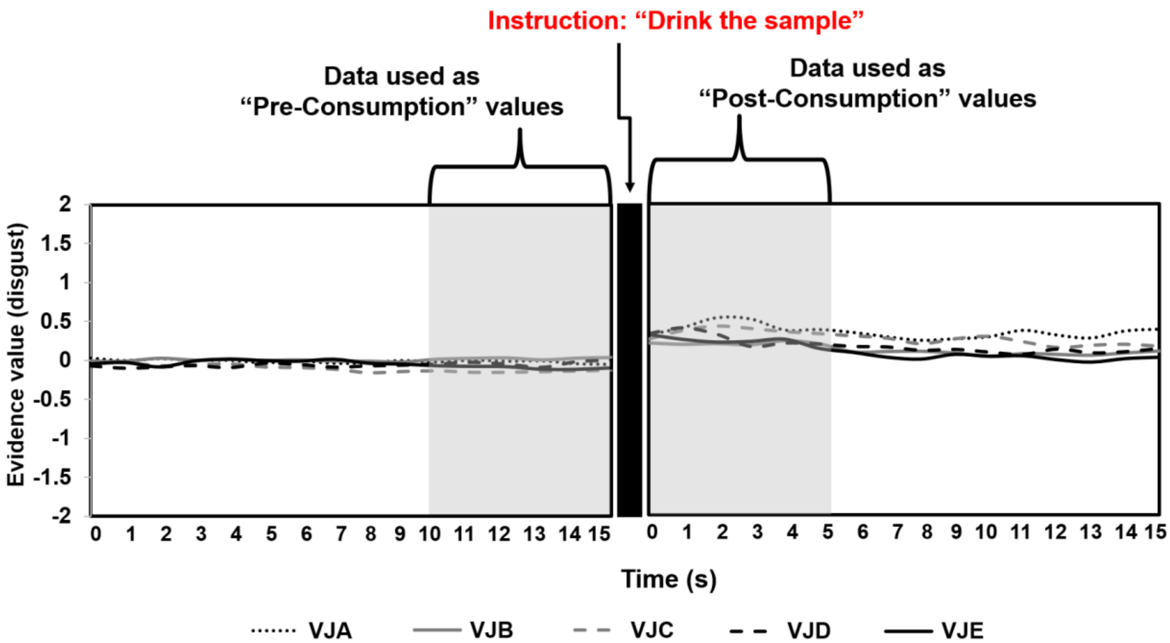
Supplementary Figure 5. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Label") and 15 s while ("Label") looking at the product label image of five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 6. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Appearance") and 10 s while ("Appearance") looking at each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 7. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Aroma") and 10 s while ("Aroma") smelling each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.



Supplementary Figure 8. Changes in evidence value of "disgust" emotion measured by facial expression analysis over 15 s before ("Pre-Consumption") and 15 s after ("Post-Consumption") tasting each five vegetable juice products: VJA, VJB, VJC, VJD, and VJE.

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Objective 6

Personality traits affect the influences of intensity perception and emotional responses on hedonic rating and preference rank toward basic taste solutions

Abstract

This study aimed at determining, based on independent predictors of taste intensity and emotional response, whether individual personality traits could affect prediction models of overall liking and preference rank toward basic taste solutions. Sixty-seven participants rated taste intensities (TI) of four basic-taste solutions at both low and high concentrations, and of plain water. Emotional responses toward each sample were measured using a self-reported emotion questionnaire (SE), facial expressions (FE), and/or autonomic nervous system responses (ANS). Participants rated overall liking of the samples and ranked their preferences. Based on the results of a hierarchical cluster analysis of five personality traits measured using the Big Five Inventory, participants were classified into two clusters: cluster N (high neuroticism) and cluster E (high extraversion). Results showed that the SE measure for both clusters N and E was better than the TI, FE, and ANS measures in explaining variances of overall liking or preference rank. A measurement of effect size found that using facial expression and/or taste intensity measures, along with self-reported emotion measure, could enhance model predictability of overall liking or preference rank toward taste samples for cluster N, while the contribution to the prediction model for cluster E was minimal. ANS measures showed little contribution to the prediction model of overall liking for either cluster. In conclusion, this study shows that personality traits, in particular traits of extraversion and neuroticism, affect not only optimum measures of emotional responses, but also modulate predicting overall liking and preference rank toward basic taste solutions.

Key-words: *Personality traits; Neuroticism; Extraversion; Taste intensity; Liking; Hedonic rating; Preference; Emotional response*

Significant Statement

This study found that emotional responses, in addition to perceived taste intensity, are effective in predicting consumer liking and preference toward tasting solutions. Interestingly, predictability levels of such measures varied with individuals' personality traits, in particular traits of neuroticism and extraversion. Furthermore, optimum measures of emotions differed with personality traits. This study suggests that food industry professionals, chemosensory researchers, and clinicians should consider personality traits of their target populations when designing beverages or tasting substances as well as when measuring liking and preference toward products.

1. Introduction

Numerous studies have shown relationships between taste intensity and acceptance (degree of liking) of taste cues among basic taste solutions, foods, and beverages (Pangborn, 1970; Mojet, Christ-Hazelhof, & Heidema, 2005; Samant, Chapko, & Seo, 2017). However, previous findings in that regard have been inconsistent probably because of different experimental conditions, as well as a variety of influential factors such as taste quality, concentration level, genetic and demographic profiles, and environmental contexts (Duffy, Peterson, Dinehart, & Bartoshuk, 2003; Mojet et al., 2005).

In addition to inducing intensity perception and hedonic response, taste cues have demonstrated potential for evoking participants' emotional responses toward basic taste solutions, foods, and beverages (Rousmans, Robin, Dittmar, & Vernet-Maury, 2000; O'Doherty, Rolls, Francis, Bowtell, & McGlone, 2001; Ng, Chaya, & Hort, 2013). Studies focusing on basic taste solutions have reported that sweet-tasting solutions evoked positive emotions, while salty-tasting solutions evoked negative emotions (Rousmans et al., 2000). Functional magnetic resonance imaging (fMRI) studies have provided supporting evidence of stimuli-induced emotional responses to taste. O'Doherty et al. (2001) showed that consumption of either sweet or salty tasting solutions resulted in pronounced neural-activations in the amygdala, a part of the brain associated extensively with emotional processing. Interestingly, similar to intensity perception-influenced acceptance of taste stimuli, taste stimuli-evoked emotional responses have been found to affect acceptance of tasting substances (Samant et al., 2017). In general, positive emotions are considered to be associated with greater levels of liking, while negative emotions are considered to be related to lower levels of liking (Ng et al., 2013; Gutjar, Dalenberg, de Graaf, de Wijk, Palascha, Renken, & Jager, 2015a).

There is growing interest in better prediction of individual variations with respect to liking and preference toward food and beverage products. Emotional responses evoked by food or beverage samples have been found to better understand individuals' liking and preference toward the samples (de Wijk, Kooijma, Verhoeven, Holthuysen, & de Graaf, 2012; Gutjar et al., 2015a; Gutjar, de Graaf, Kooijman, de Wijk, Nys, ter Horst, & Jager, 2015b). More recently, Samant et al. (2017) showed that when predicting overall liking and preference rank toward basic taste solutions, regression models using a combination of taste intensity and emotional responses performed better than did models separately using taste intensity and emotional responses. It therefore seems evident that association of taste perception and emotional responses is important to consider when seeking better understanding of individuals' liking and preference with respect to taste stimuli.

Intriguingly, it has been found that both taste perception and emotional responses are affected by individual personality traits (Stone & Pangborn, 1996; Robino, Mezzavilla, Pirastu, La Bianca, Gasparini, Carlino, & Tepper, 2016). More specifically, Stone and Pangborn (1990) demonstrated that participants who were more extroverted (or outgoing) than introverted (or reserved) liked a sweeter lemonade taste. It has also been shown that higher levels of neuroticism were associated with a greater preference for salty and sweet-tasting substances (Kikichi & Wataname, 1999), while lower levels of psychological openness were related to lower preference for sweet-tasting substances (Saliba et al., 2009). More recently, Robino et al. (2016) showed associations of alexithymia (i.e., a personality trait attributed to inhibition or inability to identify and state felt emotions) with intensity perception and acceptability of bitter-tasting compounds such as 6-n-propylthiouracil (PROP). Their results showed that, in addition to PROP non-tasters exhibiting higher alexithymia scores than PROP tasters, individuals with higher alexithymia scores showed lower preference for bitter-tasting vegetables, suggesting that the negative aspect of bitter taste perception might be mediated by personality traits such as alexithymia.

Previous studies have demonstrated that personality traits can influence emotional processing and expressiveness as well as sensory perception (Riggio & Riggio, 2002). Among the set of personality traits identified by these studies, five primary traits have been popularly accepted: “extraversion (versus introversion)”, “agreeableness (versus antagonism)”, “conscientiousness (versus lack of direction)”, “neuroticism (versus emotional stability)”, and “openness (versus closedness to experience)” (Goldberg, 1990; John & Srivastava, 1999). Among these five traits, extraversion and neuroticism have been extensively studied with respect to their influence on emotional responses. “Extraversion” is associated with being more outgoing and sociable, while “neuroticism” is associated with being more moody, irritable, and anxious (John & Srivastava, 1999). Corresponding to the natural disposition of these traits, previous studies have shown that extraversion responds strongly to brain signals regulating behavioral activation systems based on reward perception, while neuroticism responds strongly to such signals regulating behavioral inhibition systems based on punishment perception. It is therefore possible that individuals exhibiting high extraversion and neuroticism might be more predisposed toward pronounced positive emotions and negative emotions, respectively (Costa & McCrae, 1980; Verduyn & Brans, 2012). Brain imaging studies have also revealed that individuals with higher extraversion showed greater amygdala-activation in response to positive stimuli such as images of happy expressions (Canli, Sivers, Whitfield, Gotlib, & Gabrieli, 2002), while those with higher neuroticism showed greater amygdala-activation in response to negative stimuli such as facial images depicting anger, fear, and sadness (Canli, 2004). Although previous studies have indicated that these trends have not always been consistent, a key takeaway from them is that emotional responses toward specific stimuli can vary as a function of personality traits, especially neuroticism and extraversion traits. However, studies focusing on personality differences in processing of emotions elicited by taste stimuli are admittedly scarce.

As mentioned above, Samant et al. (2017) developed optimum models for predicting overall liking (rating-based data) and preference rank (choice-based data), based on taste intensity and evoked emotions, for basic taste solutions. As a continuation of the previous study, this study aimed to determine whether contributions of taste intensity and evoked emotions to prediction models related to overall liking and preference rank among basic taste solutions could differ with individual personality traits. It has previously been thought that liking ratings provide information about acceptance of samples, whereas preference ranks provide insight into choice (Meilgaard, Civille, & Carr, 2015). Thus, models predicting both overall liking and preference rank were considered in this study.

2. Materials and Methods

This study was conducted following the protocol approved by the Institutional Review Board of the University of Arkansas (Fayetteville, AR, USA). Prior to participation each participant was informed in detail about the experimental procedure and a written consent was obtained from each participant.

2.1. Participants

The study was conducted over a span of three sessions, with the first two (Sessions 1 and 2; for details, see below) one week apart. Participants were then asked to return on a subsequent day (Session 3), two to three weeks after the end of Session 2, to complete a questionnaire related to personality traits (the Big Five Inventory; for details, see below). While a total of 102 volunteers had participated in both Sessions 1 and 2 (Samant et al., 2017), 67 volunteers [36 men and 31 women; mean age ± standard deviation (SD) = 41 ± 15 years] completed all three sessions. In other words, 35 volunteers who had completed both Sessions 1 and 2 did not return to participate in Session 3 probably due to a longer time-interval between Sessions 2 and 3 and/or personal time-conflicts. Therefore, only data of the participants (N = 67) who completed all three sessions were used in this study.

The participants were recruited through the University of Arkansas Sensory Service Center database that included consumer profiles of 6,200 Northwest Arkansas residents. To minimize potential influences of mental stress on intensity perception and acceptability (Samant, Wilkes, Odek, & Seo, 2016), volunteers who had a high level of chronic stress, i.e., those who scored higher than 25 points on the 10-item Perceived Stress Scale (PSS) (Cohen, Kamarch, & Mermelstein, 1983), were not included. In addition, participants who self-reported as having known food allergies, smell or taste disorder, or clinical histories of major diseases were not included in this study. Demographic profiles of participants are shown in Table 1. As described above, the participant sample (N = 67) was composed of a similar number of men (N = 36, 54%) and women (N = 31, 46%).

2.2. Sample preparation

Tasting samples for this study included sweet, sour, salty, and bitter-tasting solutions prepared at two different concentration levels, “low” and “high”, corresponding to numerical ratings of “5” and “10”, respectively, on the universal reference scale ranging from 0- to 15-point (Meilgaard et al., 2015). According to the Spectrum method (Sensory Spectrum Inc., Chatham, NJ, USA), the four taste solutions have been found to produce iso-intensities at either low (5-point) or high (10-point) concentrations (Meilgaard et al., 2015). Numerical ratings of “low” and “high”, respectively, corresponding to the concentration levels for each taste solution, were: sweet (5% and 10% w/v), sour (0.10% and 0.15% w/v), salty (0.35% and 0.55% w/v), and bitter (0.08% and 0.15% w/v) (Meilgaard et al., 2015). Sweet, sour, salty, and bitter-tasting solutions used in this study were prepared with pure cane sugar (Great Value™, Wal-Mart Stores, Inc., Bentonville, AR, USA), citric acid (Sigma-Aldrich Fine Chemicals, St Louis, MO, USA), salt (Morton Salt, Inc., Chicago, IL, USA), and caffeine (Aldrich Chemical Company, Inc., Milwaukee, WI, USA), respectively. Spring water (Mountain Valley Springs Co., LLC Hot springs, AR, USA) was included as a control. All samples were served in 60-mL soufflé cups (Pettus Office Products, Little Rock, AR, USA) at room temperature (approximately, 23 °C).

2.3. Measurement of taste intensity and overall liking

Participants rated their perceived taste intensities on 15-cm line scales ranging from 0 (extremely weak) to 15 (extremely strong). Levels of overall liking of the samples were measured using traditional 9-point hedonic scales ranging from 1 (dislike extremely) to 9 (like extremely).

2.4. Measurement of emotional responses

2.4.1. Self-reported emotions (SE)

Self-reported emotions were measured using EsSense25 (25 items) (Nestrud, Meiselman, King, Lesher, & Cardello, 2016), a reduced version of the EsSense Profile® (39 items) designed for measuring short and relatively intense emotional responses toward consumer products including foods and beverages (King & Meiselman, 2010). The 25 emotions measured in this study were: “active”, “adventurous”, “aggressive”, “bored”, “calm”, “disgusted”, “enthusiastic”, “free”, “good”, “good natured”, “guilty”, “happy”, “interested”, “joyful”, “loving”, “mild”, “nostalgic”, “pleasant”, “satisfied”, “secure”, “tame”, “understanding”, “warm”, “wild”, and “worried” (Nestrud et al., 2016). Participants rated each item on EsSense25 on a 5-point scale ranging from 1 (not at all) to 5 (extremely).

2.4.2. Facial expression (FE) analysis

Facial expression software (version 6.1, iMotions, Inc., MA, USA) was used for recording and analyzing facial expressions. This software tracked (at a sampling rate of 102.4 Hz) the presence of seven basic universal expressions of human emotions (i.e., joy, anger, surprise, fear, contempt, disgust, and sadness) and reported an “evidence value” (EV) associated with each emotion. According to iMotions (2017), these EVs represent on a logarithmic (base 10) scale the odds of an emotion being present in a participant’s facial expression when compared to his or her neutral state. For example, a positive (or negative) EV of q for the “disgust” emotion evaluated by a human coder, indicates that expression is 10^q times more (or less) likely to be categorized as disgusting compared to a neutral state.

2.4.3. Physiological autonomic nervous system (ANS) measures

Autonomic nervous system responses (ANS) measured included heart rate (HR; unit: beats/minute), skin temperature (ST; unit: °C), and skin conductance response (SCR; unit: μSiemens), measured using a SHIMMER™ sensor (SHIMMER™, Dublin, Ireland), a flexible and non-invasive sensing platform (Burns et al., 2010). Previous research has suggested that emotional experiences could be manifested as changes in these ANS parameters (Kreibig, 2010). As explained in a previous study (Samant et al., 2017), HR was measured by placing an electrode on the proximal phalanges of the participants' ring finger, while SCR was measured by placing two Velcro-strap electrodes on the proximal phalanges of index and middle fingers of the non-dominant hand of the participant. Both HR and SCR were measured at a sampling rate of 102.4 Hz. ST (unit: °C) was also measured every 0.2 s using an eSense Skin Temperature Sensor for Android devices (Mindfield® Biosystems Ltd., Gronau, Germany) placed on the palm of participants' non-dominant hand.

2.5. Measurement of personality traits

The Big Five Inventory (BFI), consisting of 44 items representing the big five variables of personality, i.e., extraversion, agreeableness, conscientiousness, neuroticism and openness, was used in this study to determine participants' personality traits (John, Donahue & Kentle, 1991). Participants rated how much they disagreed/agreed with each of 44 items on a 5-point scale (1: disagree strongly; 5: agree strongly).

2.6. Procedure

As described above, the first two of three sessions (Sessions 1 and 2) were one week apart, and participants were then asked to participate in Session 3 by completing the questionnaire of personality traits (BFI) two to three weeks after the end of Session 2.

2.6.1. Sessions 1 and 2

All participants were asked to abstain from eating, drinking (except water), and cigarette smoking for 2 h prior to their participation to avoid potential impacts of those activities on sensory perception and acceptance (Cho et al., 2017). At each session, there were two stages of measurement, i.e., overall liking and preference rank, and further described as follows:

Overall liking measurement

Prior to starting, the experimental procedure was explained to each participant. Participants were asked to complete the EsSesne25 questionnaire by rating how much of each emotion he/she felt at that moment. Participants' facial expressions were measured by a camera (Logitech Europe S.A., Nijmegen, Netherlands) placed in front of their faces to provide a clear view. Before placing the SCR electrodes, participants' hands were thoroughly cleaned with 70% (v/v) isopropanol (PL developments, Clinton, SC, USA) and a conductive cream was smeared over the proximal phalanges of index and middle fingers on their non-dominant hands. Electrodes for measuring SCR, HR, and ST were attached to the non-dominant hand of each participant. Participants were asked to keep their hand movements to a minimum during the experiment to avoid generation of noise in the FE and ANS data.

At each session, participants were asked to taste five samples: four tasting-samples (sweet, sour, salty, bitter-tasting solutions at either low or high concentration) and spring water as a control; all participants therefore tasted ten samples over the span of two sessions. While the control sample (spring water) was presented during both sessions, presentation order of the other four taste solutions was randomized and counter-balanced during both sessions.

Each sample (approximately 45-mL) was presented in a 60-mL soufflé cup identified with a three-digit code. Participants were asked to pour the entire sample into their mouth and swallow it while looking at the camera. To ensure representative data, FE and ANS were measured 15 s before the sample was poured into their mouths and 15 s after they had swallowed the samples (see Figures 2 and 3 in Samant et al., 2017). Participants were then asked to rate the perceived intensity and overall liking of each sample on a 15-cm line scale and a 9-point hedonic scale, respectively (see section 2.3). A two-minute break was given between sample presentations to nullify carryover effects.

Preference rank measurement

After tasting all five samples at each session, participants took a ten-min break after which they were taken to a different room to re-taste the five samples. To minimize learning-related effects, samples were labeled with different three-digit codes. After re-tasting all samples, participants ranked them in order of preference (1: most preferred; 5: least preferred). During the preference rank task, taste intensity and emotional responses toward taste stimuli were not measured.

2.6.2. Session 3

Participants were asked to return to complete the BFI questionnaire two to three weeks after completion of Session 2. A longer time-interval between Sessions 2 and 3 was expected to minimize any associations between the measurements of emotional responses and personality traits. Completion of the BFI questionnaire took an average of 10 min. The rating of each personality trait was calculated for every participant using guidelines provided by John and Srivastava (1999).

2.7. Data analysis

2.7.1. Self-reported emotions (SE)

Since the primary goal of this study was to measure emotions elicited by the taste solutions, ratings of each emotion obtained before beginning the study were subtracted from those obtained after consumption of each sample and subsequent statistical analysis was performed using the subtracted values.

2.7.2. Facial expression (FE) and autonomic nervous system responses (ANS)

Differences between before and after consumption of each sample with respect to FE (represented by the evidence values of 7 emotions) and ANS (represented by SCR, HR, and ST) were determined. Based on a previous study (Samant et al., 2017), the first 5 s measures of the FE and ANS, respectively, from the 15 s measurement-interval before consumption, were considered as “pre-consumption” values for each response. While changes in emotions measured by FE exhibited maximum variation during the first 5 s after consumption, the maximum variation in ANS (SCR, HR, and ST) lasted for more than 10 s after consumption. This is possibly because autonomic nervous system responses have been associated with delayed onset compared to facial expressions with quicker onset (Danner, Sidorkina, Joechl, & Duerrschmid, 2014). The first 5 s of FE and the 10 s of ANS (SCR, HR, and ST, respectively) from the 15 s measurement after consumption of each sample were therefore considered as "post-consumption" values for each response. The "post-consumption" values for FE and ANS were subtracted from the "pre-consumption" values for each sample, and the differences were used for subsequent statistical analysis.

2.7.3. Statistical analysis

Data was analyzed using JMP® Pro software (version 13.0, SAS Institute Inc., Cary, NS, USA). A hierarchical cluster (HC) analysis for the BFI data was performed using Ward's method (Ward, 1963). Ward's method, one of most popular agglomerative algorithms, has been found to be most suitable for studies where 1) the number of sample-observations in each cluster are expected to be similar and 2) there are no outlier sample-observations. Ward's method is considered to be sensitive to outliers (Milligan, 1980; Punj & Stewart, 1983; Ketchen, Jr. & Schook, 1996). To reduce a potential influence of outliers (Ketchen, Jr. & Schook, 1996), the HC analysis was performed on the standardized data in this study. Ward's method was also chosen as an agglomerative algorithm to minimize the impact of sample-observation size (i.e., the number of participants) in each cluster with respect to the prediction models of overall liking or preference rank, because Ward's method is likely to produce clusters with an approximately equal number of sample-observations (Ketchen, Jr. & Schook, 1996). Based on both a dendrogram and a constellation plot (Supplementary Figure 1) drawn by the HC analysis, 67 participants were classified into two major clusters (for details, see section 3.1.). A Student's *t*-test and a chi-square test were performed to determine whether the two clusters differed with respect to personality traits and demographic profiles, with statistical significance established at $P < 0.05$. In addition, a two-way analysis of variance (ANOVA), treating cluster (i.e., clusters N and E) as a fixed effect and participants as a random effect, and a Mann-Whitney *U*-test were conducted to determine whether the two clusters could differ in terms of overall liking and preference rank toward each taste stimulus.

A stepwise multiple linear regression analysis and an ordinal logistic regression analysis were conducted to predict overall liking and preference rank, respectively, of the basic taste solutions. Specifically, dependent variables chosen in the model were overall liking and rank (fitted separately), with all other variables (taste intensity, 25 self-reported emotions on EsSense25, 7 basic emotions in facial expression, and SCR, HR, and ST parameters in ANS) used as independent variables. Since the primary aim of the study was to compare the model prediction performance between clusters in terms of predictive values of independent variables, and to find an optimum model, we constructed a total of eight statistical models for each dependent variable, i.e., overall liking and preference rank for each cluster. More specifically, each of the eight statistical models used either a sole or a combination of independent variables as follows: 1) taste intensity (TI); 2) twenty-five self-reported emotions (SE); 3) seven emotions in facial expression (FE); 4) SCR, HR, and ST measures in autonomic nervous system responses (ANS); 5) TI and SE; 6) TI and FE; 7) SE and FE; and 8) TI, SE, and FE. Since ANS measures made no contribution to the prediction models (see sections 3.2. and 3.3.), ANS measures were not further used as independent variables along with other measures (TI, SE, and FE).

An optimum variable selection was performed using the *P*-value stopping criterion, with probabilities for a predictor (independent variable) of entering and leaving the model set to 0.25 and 0.05, respectively. In each model, for each predictor, parameter estimates (β), corresponding standard errors, and levels of significance were reported. Variable inflation factor (VIF) values were ensured to be less than 3, indicating low multi-collinearity among predictors (Klimberg & McCullogh, 2013). Models constructed for prediction of overall liking using a multiple linear regression approach were compared using adjusted R^2 (R^2_{adj}), root mean square error (RMSE), Mallows' Cp, total number of predictors in the model (p), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC). Models constructed for prediction of preference rank using a multiple ordinal logistic regression approach were compared using parameters such as R^2, *-log-likelihood*, AICc, and BIC. These parameter choices have been extensively used for model comparison in previous studies (Montgomery, Peck, & Vining, 2015; JMP®, 2013), and it should be noted that the above-mentioned models were separately constructed for each cluster.

Cohen's f^2 was calculated as an effect size index for comparing R^2_{adj} values associated with the prediction models within clusters using Cohen's formula: $f^2 = (R^2_{adjAB} - R^2_{adjA})/(1-R^2_{adjAB})$, where B is the variable of interest (e.g., facial expressions) and A is another variable (e.g., self-reported emotions). R^2_{adjAB} is the proportion of variance accounted for by A and B together (when compared to a model without any regression variables, i.e., a model with only intercept) and R^2_{adjA} is the proportion of variance accounted for by variable A (when compared to a model without any regression variables, that is, a model with only intercept). Therefore, the numerator of the equation represents the proportion of variance uniquely accounted for by variable B (Selya et al., 2012). For multiple linear regression, it has been suggested that Cohen's f^2 = 0.15, 0.20, and 0.35 reflect small, moderate, and large differences among the models. In other words, a higher value of f^2 suggests a higher importance of variable B in the model AB (Selye et al., 2012).

3. Results

3.1. Characteristics of cluster N (high neuroticism) and cluster E (extraversion)

Based on both a dendrogram and a constellation plot (Supplementary Figure 1) of the HC analysis using Ward's method for the BFI data, 67 participants were classified into two clusters. Cluster N (N = 30; 16 men and 14 women) and cluster E (N = 37; 20 men and 17 women) differed significantly as a function of personality traits. More specifically, cluster N was significantly higher than cluster E with respect to the neuroticism trait ($P < 0.001$). In addition, participants in cluster E were more extroverted ($P < 0.001$) and open ($P = 0.022$) compared to those in cluster N. The two clusters did not differ in terms of conscientiousness ($P = 0.789$) and agreeableness ($P = 0.086$) traits.

Table 1 shows the demographic profiles of the two clusters. A Student's *t*-test revealed that the two clusters did not differ significantly in terms of mean age ($P = 0.648$), total number of people living in the household including oneself ($P = 0.185$), or total number of children younger than 18 years of age living in the household ($P = 0.452$). In addition, chi-square tests found that the two clusters did not differ significantly in terms of gender ratio (P = 0.953), education level (P = 0.829) or annual income level (P = 0.593).

3.2. Comparisons of cluster N (high neuroticism) and cluster E (high extraversion) in the prediction model of overall liking developed using taste intensity, self-reported emotions, facial expressions, and autonomic nervous system responses

Figure 1 shows that clusters N and E were not significantly different with respect to overall liking of each taste stimulus (P > 0.05), except sour taste solution at a high concentration level (P = 0.032).

Optimum prediction models of overall liking toward the taste stimuli and their significant predictors were found to vary as a function of personality traits. Table 2 shows that taste intensity (model "A") explained 20% and 13%, respectively, of variances in overall liking for cluster N (RMSE = 1.97) and cluster E (RMSE = 2.02). The contribution of self-reported emotions (model "B") with respect to explaining the variances in overall liking was slightly greater for cluster E (R^2_{adj} = 0.48, RMSE = 1.57) than for cluster N (R^2_{adj} = 0.42, RMSE = 1.68). As shown in Table 3 (model "B"), 5 out of 25 self-reported emotions were found to be significant predictors of overall liking for cluster N: "disgusted", "secure", "satisfied", "active", and "pleasant". For cluster E, 4 emotions were found to be significant predictors of overall liking (model "B" in Table 4): "disgusted", "satisfied", "nostalgic", and "calm".

Unlike the contributions of self-reported emotions, the contribution of facial expressions (model "C" in Table 2) to explain variances in overall liking was greater for cluster N (25%, R^2_{adj} = 0.25, RMSE = 1.90) than for cluster E (18%, R^2_{adj} = 0.18, RMSE = 1.96). As shown in “model C” of Table 3, among participants in cluster N, 5 out of 7 emotions measured in terms of EV were found to be significant variables: “EV disgust”, “EV contempt”, “EV fear”, “EV sadness”, and “EV surprise”. For participants in cluster E, only 3 emotions measured using facial expressions were significant in the prediction model for overall liking (model “C” in Table 4): “EV disgust”, “EV contempt”, and “EV sadness”.

SCR, HR, and ST measures of ANS (model “D” in Table 2) made no contribution in predicting overall liking of the basic taste solutions for either cluster. Because they made no contribution to the prediction models, ANS measures were not used as independent variables in further analysis.

As described above, self-reported emotions (SE) could explain the highest proportions of variances in the prediction models of overall liking for both clusters (42% for cluster N and 48% for cluster E). Using the equation described in section 2.7.3, Cohen’s f^2 using R^2_{adj} values of model “B” (self-reported emotions) and model “G” (self-reported emotions and facial expressions) was calculated to determine whether adding measures of facial expressions was important for improving the model’s predictability with respect to overall liking of taste solutions. Cohen’s f^2 values were 0.21 and 0.02 for clusters N and E, respectively, indicating that adding the measures of facial expressions could enhance predictability of overall liking of taste solutions for cluster N, but not for cluster E. In addition, Cohen’s f^2 using R^2_{adj} values of model “B” (self-reported emotions) and model “E” (X: taste intensity and self-reported emotions) were calculated to determine whether adding measures of taste intensity was important with respect to enhancing model predictability. Cohen’s f^2 values were 0.12 and nearly 0 for clusters N and E, respectively, indicating that adding measures of taste intensity can slightly better predict overall liking of taste solutions for cluster N, but not for cluster E. Interestingly, the effect sizes of adding measures of taste intensity to the model using both self-reported emotions and facial expressions (model “H”) (taste intensity, self-reported emotions, and facial expressions) when compared to model “G” (self-reported emotions and facial expressions) were 0.04 and nearly 0, respectively, for clusters N and E.

3.3. Comparisons of cluster N (high neuroticism) and cluster E (high extraversion) in the prediction model of preference rank developed using taste intensity, self-reported emotions, facial expressions, and autonomic nervous system responses

Mann-Whiney *U*-test revealed that clusters N and E were not significantly different with respect to preference rank sum toward each taste stimulus: bitter taste at low ($P = 0.441$) and high ($P = 0.767$) concentration levels; salty taste at low ($P = 0.952$) and high ($P = 0.751$) concentration levels; sour taste at low ($P = 0.663$) and high ($P = 0.566$) concentration levels; sweet taste at low ($P = 0.676$) and high ($P = 0.306$) concentration levels; and water tested in both low ($P = 0.421$) and high ($P = 0.447$) concentration sessions.

Optimum prediction models of preference rank toward the taste stimuli and their significant predictors were found to vary as a function of personality traits. Table 5 shows that taste intensity (model “A”) explained 5% and 3%, respectively, of variances in preference rank for clusters N and E. In addition, self-reported emotions (model “B”) accounted for 7% and 8%, respectively, of variances in preference rank for clusters N and E. As shown for model “B” in Tables 6 and 7, only 2 self-reported emotions, i.e., “disgusted” and “satisfied”, were found to be significant predictors of preference for clusters N and E.

Facial expressions (model “C” in Table 5) accounted for 5% of variance in preference rank for cluster N, but for only 2% in cluster E. For cluster N, 4 out of 7 emotions measured using facial expression analysis were found to be significant predictors of preference rank (model “C” in Table 6): “EV disgust”, “EV contempt”, “EV anger”, and “EV sadness”. Only 2 emotions were found to be significant predictors of preference rank for cluster E (model “C” in Table 7): “EV disgust” and “EV sadness”.

Similar to the case for overall liking, since ANS measures made no contribution to predicting preference rank of the basic taste solutions for either cluster (model “D” in Table 5), they were not used as independent variables in further analysis.

3.4. Comparisons between cluster N (high neuroticism) and cluster E (high extraversion) with respect to optimal model selection of overall liking

Table 2 shows model comparison parameters for each model constructed for overall liking for clusters N and E. Multiple linear regression model “H”, based on a combination of taste intensity, self-reported emotions, and facial expressions, produced the highest R^2_{adj} (0.54) with the lowest RMSE (1.49) and lower values of AICc (1103.46) and BIC (1146.82) for cluster N. As shown in Table 3, for cluster N, significant predictors of optimum model “H” were taste intensity ($\beta = -0.11$, $P < 0.001$) and self-reported emotions such as “active” ($\beta = 0.32$, $P < 0.001$), “disgusted” ($\beta = -0.74$, $P < 0.001$), “enthusiastic” (β = -0.26, $P = 0.009$), “good” ($\beta = 0.30$, $P = 0.023$), “pleasant” ($\beta = 0.24$, $P = 0.029$), “satisfied” ($\beta = 0.36$, $P < 0.001$), and “secure” ($\beta = -0.50$, $P < 0.001$), along with facial expressions (EV) of “EV disgust” (β= -0.28, $P < 0.001$) and “EV sadness” ($\beta = -0.56$, $P < 0.001$).

For cluster E, the model using self-reported emotions and facial expressions (model "G") was found to be optimum [R^2_{adj} = 0.49, RMSE = 1.53, AICc = 1383.72, BIC = 1410.81]. For cluster E, significant predictors of optimal model "G" were self-reported emotions such as "calm" (β = -0.21, P = 0.005), "disgusted" (β = −1.01, P < 0.001), "nostalgic" (β = 0.21, P = 0.035) and "satisfied" (β = 0.50, P < 0.001), along with facial expressions (EV) of "EV disgust" (β= -0.22, P = 0.008) (Table 4).

3.5. Comparisons between cluster N (high neuroticism) and cluster E (high extraversion) with respect to optimal model selection of preference rank

Table 5 shows model comparison parameters for each model constructed for preference rank for clusters N and E, respectively. Similar to overall liking, ordinal logistic regression model "H" for predicting preference rank, using a combination of taste intensity, self-reported emotions, and facial expressions, was found to be optimum for cluster N. This model produced the highest R^2 (0.1) as well as lower values in *-log-likelihood* (433.58), AICc (883.65), and BIC (912.79). Significant predictors for this model were taste intensity (β = −0.13, P < 0.001) and self-reported emotions such as "disgusted" (β = −0.56, P < 0.001), "good" (β = 0.33, P = 0.013), along with facial expressions of "EV sadness" (β = -0.44, P = 0.005) (Table 6).

For cluster E, model "E" that predicted preference rank using taste intensity and self-reported emotions was found to be optimum since it produced the highest R (0.08) as well as lower values in *-log-likelihood* (547.89), AICc (1110.1), and BIC (1137.18) (Table 5). Significant predictors of the model "E" were taste intensity (β = −0.06, P = 0.019) and self-reported emotions such as “disgusted” ($\beta = -0.61$, $P < 0.001$) and “satisfied” ($\beta = 0.27$, $P = 0.006$) (Table 7).

4. Discussion

The results from this study showed no significant differences between clusters N (high neuroticism) and E (high extraversion) with respect to overall liking and preference rank toward basic taste solutions at two concentration levels, except overall liking of sour taste solution at a high concentration level. These findings indicate that personality traits, in particular high neuroticism versus high extraversion, are unlikely to influence overall liking and preference rank toward basic taste solutions and spring water.

This study determined whether independent variables (i.e., taste intensity, self-reported emotions, facial expressions, and ANS measures) and their degrees of contributions to optimum prediction models of overall liking and preference rank toward basic taste solutions could differ as a function of personality traits. The results from this study revealed that, among the independent variables of models, self-reported emotions accounted for the largest proportion of variations with respect to overall liking and preference rank among participants in cluster N and among those in cluster E (model “B” in Tables 2 and 5). However, adding facial expressions to the model was beneficial with respect to predicting overall liking for cluster N, but not for cluster E (as indicated by effect sizes of 0.21 versus 0.02, respectively) (see model “G” in Table 2). In other words, for cluster N (high neuroticism) a combination of facial expressions and self-reported emotions provided a moderately better model compared to one with only self-reported emotions. However, for cluster E (high extraversion) the combination of facial expressions and self-reported emotions provided little advantage over the model with only self-reported emotions. This result is in accordance with meta-analysis results of previous studies that investigated the association between personality traits and emotional expressiveness using self-reported questionnaires along with behavioral techniques such as facial expressions (Riggio & Riggio, 2002). In that study, extraversion was more strongly related to emotion expressivity measured using self-reported techniques than to emotion expressivity measured by behavioral techniques such as facial expressions (Riggio & Riggio, 2002); emotion expressiveness herein is defined as how well a subject can communicate his/her feelings non-verbally. Neuroticism exhibited no relationship with emotional expressivity using self-reported measures, while its association with emotion expressiveness using behavioral measures was slightly unclear (Riggio & Riggio, 2002). A recent study found that neuroticism has a strong positive association with an alexithymia trait, i.e., the personality trait describing inhibition or inability to express how one is feeling (Heshmati & Azmoodeh, 2017). It can therefore be suggested that a higher level of neuroticism could be associated with lower ability of an individual to explicitly express how he/she feels. In this way, using implicit methods such as facial expression analysis might provide a better understanding of how individuals with a high level of neuroticism emotionally react to specific stimuli including tasting substances.

Personality differences relating to effectiveness of participants in expressing their emotions also depend on valence of the emotion, i.e., whether the target emotion is positive or negative. There is extensive research suggesting that participants with a high level of extraversion are predisposed toward positive emotions, while participants with a high level of neuroticism are predisposed toward negative emotions (Costa & McCrae, 1980; Canli, Zhao, Desmond, Kang, Gross, & Gabrieli, 2001; Canli et al., 2002; Canli, 2004; Verduyn & Brans, 2012). In a year-long study conducted by Costa and McCrae (1980), extraversion and neuroticism traits, measured by both the Cattell Sixteen Personality Factor Questionnaire (Cattell, Eber & Tatsuoka, 1970) and the Eysenck Personality Inventory (EPI; Eyesenck & Eyesenck, 1964), were positively correlated to positive and negative affect scores, respectively. In fact, it has been suggested that extraversion and neuroticism affect the brain functioning in a different manner (Fisher, Wilk & Fredrikson 1997). A study by Canli (2004) measured amygdala activations in response to emotionally negative and positive images (taken from International Affective Picture Series). Interestingly, participants with a higher level of extraversion showed greater amygdala activation to positive pictures than to negative ones, while conversely participants with a higher level of neuroticism showed greater amygdala activation to negative images than to positive ones. Similar results have been reported in other studies using positive (e.g., ice cream and brownie) and negative (e.g., cemetery) images (Canli et al., 2001). In another brain-imaging study (Canli et al., 2002), when participants viewed images of faces expressing emotional (happy, sad, fearful, and angry) or neutral states, their amygdala activations in response to each visual stimulus were measured. While significant amygdala activation was found only in response to fearful emotion, amygdala activation in response to happy emotion was positively correlated to extraversion. Based on these results, two processes have been suggested as taking place in the amygdaloid region. The first of these is activation of amygdala in response to fear emotion, consistent among all participants. The second is activation of positive emotions such as happy, varying among participants as a function of extraversion (Canli et al., 2002). It is therefore increasingly evident that clusters N and E might have a higher likelihood of expressing negative and positive emotions, respectively.

Intriguingly, it has been suggested that self-reported emotion questionnaires developed to measure food-evoked emotions should have more positive terms than negative terms (Desmet & Schifferstein, 2008). This is attributed to the fact that consumption of food is expected to evoke positive or at least neutral emotions (Gibson, 2007). On the other hand, studies performing facial expression analysis have shown greater reliability when measuring negative emotions than when measuring positive emotions (Zeinstra, Koelen, Colindres, Kok, & de Graaf, 2009). This might explain why cluster E participants in this study, who exhibit inherently stronger tendencies to feel positive emotions (compared to introverts), expressed strongly their feelings toward the taste stimuli via a self-reported emotional questionnaire. However, cluster N might be pre-disposed to express negative more than positive emotions that could be effectively captured by facial expression analysis. It should be noted that cluster E did not contain 100% extroverts and cluster N did not contain 100% neurotics, so while we saw the important contribution of self-reported emotions to predicting overall liking and preference rank among both clusters N and E, the contribution of facial expressions should also be taken into account especially for participants exhibiting high levels of neuroticism. Moreover, since neurotic participants are said to be moody and not emotionally stable (John & Srivastava, 1999), relying only on their self-reported responses might not provide a good predictor of how they truly feel toward a stimulus. Since facial expression software captures involuntary emotional reactions (iMotions, 2017), such measurements might strengthen the prediction model.

The relationship of personality traits to taste perception is not as clear as is its association with emotional processing. Most previous studies have focused on understanding the influence of personality traits on individual choices and preferences in terms of taste quality (e.g., sweet, salty, bitter, sour tastes) rather than intensity. Another study that investigated the role of extraversion level on intensity perception of taste stimuli found no clear association between extraversion and taste intensity perception (Zverev & Mipando, 2008). In the present study, taste intensity had a small to moderate contribution with respect to predicting overall liking for cluster N, while for cluster E this contribution was minimal (Table 2).

This study developed optimum models for predicting overall liking and preference by comparing different combinations of predictors including taste intensity and emotional responses for both clusters. For cluster N, the model predicting overall liking using self-reported emotions and facial expressions (model “G”) had a high R^2_{adj}, with low values for RMSE, AICc and BIC. Adding taste intensity to this model (model “H”) slightly increased R^2_{adj} while further lowering RMSE, AICc, and BIC values. Although Cp for model “G” was low, model “H” was still retained since the other model parameters were optimized in that model (Table 2). For cluster E, the prediction model “B” of overall liking, using only self-reported emotions, had a reasonably high R^2_{adj} value and low values of RMSE, AICc, and BIC. However, adding facial expressions to the model (model “G”) increased the R^2_{adj} slightly with decreasing RMSE, AICc, and BIC values. Therefore, while either model “B” or model “G” should work, the latter (“G”) was chosen due to its slightly higher R^2_{adj}. Even though the optimum model chosen for cluster E included facial expressions, it should be noted that its contribution to model “”G” was lower than for cluster N (Table 2). With respect to preference rank, model “H”, developed using self-reported emotions, facial expressions, and taste intensity, was found to be optimum for cluster N, while for cluster E model "E" using taste intensity and self-reported emotions was optimum (Table 5). These models maximized R^2 with the lowest values of *-log-likelihood*, AICc, and BIC.

Notably, model predictability of preference ranks (Table 5) was smaller than that of overall liking ratings (Table 2) toward taste samples evaluated in this study. This might be interpreted as an indication that preference rank judgement is influenced by other factors rather than only by sensory and emotional responses (Köster, 2009). In a previous study by Lévy and Köster (1999), when participants were asked to perform both liking and preference tests toward the same beverage samples, more than 30% of the participants exhibited differing patterns among the results. In particular, consumer preference for identical samples was found to change within a session as well as between sessions (Lévy & Köster, 1999), reflecting difficulty in predicting consumer preference. Another plausible explanation for the smaller predictability of preference rank models is that independent variables (taste intensity, self-rated emotions, facial expressions, and autonomic nervous system responses) used in the preference rank models were obtained during overall liking measurements of taste samples, possibly leading to greater model predictability of overall liking ratings. In addition, since preference rank measurement was performed in a different room, potential influences of environmental contexts might not be negligible.

Gender differences have been found in personality dimensions, especially neuroticism and extraversion (Lynn & Martin, 1997). Lynn and Martin (1997) reported gender differences with respect to neuroticism, extraversion, and psychoticism measured by the Eysenck Personality Inventory across 37 countries. It was found that while women, in comparison to, scored higher on neuroticism traits in all 37 countries, men scored higher on psychoticism and extraversion traits in more than 30 countries. In another study by Weisberg, DeYoung, and Hirsh (2011), women scored higher than men in both neuroticism and extraversion traits. Such gender differences in personality traits suggest that gender may also play an important role in determining optimum measures of emotional response and taste intensity for predicting overall liking and preference rank toward tasting substances. Thus, further study with greater sample sizes that include both men and women is needed to explore the effect of gender on models for predicting overall liking of and preference rank for taste solutions.

Finally, our findings should be interpreted with caution due to a limitation of this study. When measuring facial expressions, since participants' face was occluded when the taste sample was taken into the mouth, facial expressions during the initial stages of simulation were probably missed. Because initial facial expressions and impressions toward stimuli have been found to affect overall liking of and preference for the stimuli, a lack of initial facial expressions during tasting should be considered when interpreting the results from this study.

5. Conclusion

To summarize, this study showed that prediction models for overall liking and preference rank toward taste stimuli vary as a function of personality traits. Self-reported emotions better explained variations in overall liking and preference rank among participants with either higher neuroticism or higher extraversion when compared to perceived taste intensity, facial expression-based emotions, and autonomic nervous system responses. Using facial expression and/or taste intensity measures along with self-reported emotion measures as independent predictors could contribute more to the prediction model of overall liking for participants with higher levels of neuroticism, while their contributions to the model developed for participants with higher levels of extraversion was minimal. In other words, self-reported emotions accounted for a majority of variations with respect to overall liking for extroverts, while a combination of self-reported emotions, facial expressions, and taste intensity might work better for participants with higher levels of neuroticism. In conclusion, our findings provide empirical evidence that personality traits, in particular traits of extraversion and neuroticism, affect not only optimum measures of emotional responses, but also contribute to predicting overall liking and preference rank of basic taste stimuli.

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Conflict of Interest

All authors declare that no conflict of interest exists in the conduct and reporting of this research.

Author Contributions

All authors had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. Study concept and design: S.S., H.S. Acquisition of data: S.S. Analysis and interpretation of data: S.S., H.S. Drafting of the manuscript: S.S., H.S. Critical revision of the manuscript for important intellectual content: S.S., H.S. Statistical analysis: S.S. Administrative, technical, and material support: H.S. Study supervision: H.S.

Table 1. Demographic profiles of the cluster N (high neuroticism) and cluster E (high extraversion)

	Cluster N		Cluster E	
	N	%	*N*	%
Number of participants	30		37	
Gender				
Men	16	53.3	20	54.1
Women	14	46.7	17	45.9
Mean age (± SD)	40 (± 14) years		42 (± 16) years	
Education level[1]				
High School	3	10.0	2	5.4
Some college	5	16.7	8	21.6
2-4 year college degree	15	50.0	20	54.1
Master or PhD degree	7	23.3	7	18.9
Annual income level[2]				
< $20,000	6	20.0	8	21.6
$20,000 to $39,999	10	33.3	7	18.9
$40,000 to $59,999	6	20.0	7	18.9
$60,000 to $79,999	2	6.7	6	16.2
≥ $80,000	6	20.0	9	24.4
Total number of people living in household (including yourself)	3 (± 1)		3 (± 1)	
Total number of children younger than 18 years living with yourself	1 (± 1)		1 (± 1)	

[1]: Two categories of education level, “master degree” and “doctoral or professional degree”, were combined since the number of each case was small.

[2]: Two categories of annual income level, “$80,000 to $99,999 per year” and “more than $100,000 per year”, were combined since the number of each case was small.

Table 2. Model comparison parameters for cluster N and cluster E for predicting overall liking based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variables	R^2_{adj}		RMSE		C_p		p		AICc		BIC	
			N	E	N	E	N	E	N	E	N	E	N	E
A	Overall liking	TI	0.20	0.13	1.97	2.02	2	2	2	2	1263.38	1572.92	1274.41	1584.60
B	Overall liking	SE	0.42	0.48	1.68	1.57	2.30	0.09	6	5	1169.61	1388.76	1195.15	1412.01
C	Overall liking	FE	0.25	0.18	1.90	1.96	6.17	8.11	6	4	1246.28	1555.25	1271.82	1574.65
D	Overall liking	ANS	0.00	0.00	2.20	2.16	-1.22	-1.88	1	1	1328.68	1624.27	1336.05	1632.06
E	Overall liking	TI, SE	0.48	0.48	1.60	1.55	1.17	2.9	8	6	1141.26	1384.96	1173.98	1412.05
F	Overall liking	TI, FE	0.35	0.24	1.78	1.89	6.66	4.61	7	5	1205.94	1528.01	1235.08	1551.26
G	Overall liking	SE, FE	0.52	0.49	1.53	1.55	4.61	-0.18	10	6	1121.16	1383.72	1160.98	1410.81
H	Overall liking	TI, SE, FE	0.54	0.49	1.49	1.55	6.09	1.60	11	7	1103.46	1381.64	1146.82	1412.55

R^2_{adj}: adjusted R^2; RMSE: root mean square error; Cp: Mallow's Cp; p: total number of predictors in the model; AICc: corrected Akaike information criterion; and BIC: Bayesian information criterion.

Table 3: Significant predictors of multiple regression models of overall liking for cluster N based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variable	Significant predictors[1]	Parameter estimate (β)	Standard error (SE)	*P*-value
A	Overall liking	TI	Taste intensity	-0.25	0.03	<0.001
B	Overall liking	SE	Disgusted	-1.01	0.10	<0.001
			Secure	-0.48	0.10	<0.001
			Satisfied	0.41	0.11	<0.001
			Active	0.25	0.10	0.013
			Pleasant	0.24	0.12	0.046
C	Overall liking	FE	EV Disgust	-0.63	0.09	<0.001
			EV Contempt	0.58	0.17	<0.001
			EV Fear	-0.51	0.17	0.003
			EV Sadness	-0.47	0.18	0.010
			EV Surprise	0.38	0.12	0.003
D	Overall liking	ANS	No significance			
E	Overall liking	TI, SE	Disgusted	-0.85	0.10	<0.001
			Secure	-0.51	0.10	<0.001
			Satisfied	0.32	0.10	0.002
			Active	0.28	0.09	0.004
			Pleasant	0.24	0.11	0.03
			Tame	0.20	0.09	0.03
			Taste intensity	-0.14	0.03	<0.001
F	Overall liking	TI, FE	EV Sadness	-0.57	0.17	<0.001
			EV Contempt	0.54	0.16	<0.001
			EV Fear	-0.43	0.16	0.007
			EV Disgust	-0.41	0.09	<0.001
			EV Surprise	0.27	0.12	0.02
			Taste intensity	-0.19	0.03	<0.001
G	Overall liking	SE, FE	Disgusted	-0.85	0.09	<0.001
			Secure	-0.54	0.09	<0.001
			EV Sadness	-0.50	0.14	<0.001
			Satisfied	0.42	0.10	<0.001
			EV Disgust	-0.37	0.08	<0.001
			Good	0.34	0.14	0.013
			Active	0.30	0.09	0.001
			Enthusiastic	-0.29	0.10	0.006
			Pleasant	0.23	0.12	0.043
H	Overall liking	TI, SE, FE	Disgusted	-0.74	0.09	<0.001
			EV Sadness	-0.56	0.14	<0.001
			Secure	-0.50	0.09	<0.001
			Satisfied	0.36	0.10	<0.001
			Active	0.32	0.09	<0.001
			Good	0.30	0.13	0.023
			EV Disgust	-0.28	0.08	<0.001
			Enthusiastic	-0.26	0.10	0.009
			Pleasant	0.24	0.11	0.029
			Taste intensity	-0.11	0.02	<0.001

[1]EV represents an evidence value.

Table 4. Significant predictors of multiple regression models of overall liking for cluster E based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variable	Significant predictors[1]	Parameter estimate (β)	Standard error (SE)	*P*-value
A	Overall liking	TI	Taste intensity	-0.19	0.03	<0.001
B	Overall liking	SE	Disgusted	-1.08	0.08	<0.001
			Satisfied	0.51	0.08	<0.001
			Nostalgic	0.20	0.10	0.045
			Calm	-0.20	0.08	0.008
C	Overall liking	FE	EV Disgust	-0.63	0.10	<0.001
			EV Contempt	0.55	0.14	<0.001
			EV Sadness	-0.41	0.14	0.003
D	Overall liking	ANS	No significance			
E	Overall liking	TI, SE	Disgusted	-1.01	0.09	<0.001
			Satisfied	0.50	0.08	<0.001
			Calm	-0.21	0.08	0.006
			Nostalgic	0.20	0.10	0.041
			Taste intensity	-0.05	0.02	0.016
F	Overall liking	TI, FE	EV Contempt	0.51	0.13	<0.001
			EV Disgust	-0.48	0.10	<0.001
			EV Sadness	-0.34	0.14	0.011
			Taste intensity	-0.14	0.02	<0.001
G	Overall liking	SE, FE	Disgusted	-1.01	0.08	<0.001
			Satisfied	0.50	0.08	<0.001
			EV Disgust	-0.22	0.08	0.008
			Calm	-0.21	0.08	0.005
			Nostalgic	0.21	0.10	0.035
H	Overall liking	TI, SE, FE	Disgusted	-0.96	0.09	<0.001
			Satisfied	0.49	0.08	<0.001
			Nostalgic	0.21	0.10	0.034
			Calm	-0.21	0.07	0.005
			EV Disgust	-0.19	0.08	0.021
			Taste intensity	-0.04	0.02	0.043

[1]EV represents an evidence value.

Table 5. Model comparison parameters for cluster N and cluster E for predicting preference rank based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variables	R^2		*-loglikelihood*		AICc		BIC	
			N	E	N	E	N	E	N	E
A	Preference rank	TI	0.05	0.03	458.73	577.30	927.66	1164.77	945.97	1184.18
B	Preference rank	SE	0.07	0.08	447.64	550.55	907.56	1113.33	929.49	1136.58
C	Preference rank	FE	0.05	0.02	457.76	585.32	932.02	1182.88	961.15	1206.13
D	Preference rank	ANS	0.00	0.00	482.83	595.49	973.80	1199.09	988.48	1214.64
E	Preference rank	TI, SE	0.09	0.08	437.69	547.89	889.77	1110.1	915.31	1137.18
F	Preference rank	TI, SE, FE	0.08	0.03	446.23	574.77	908.96	1161.76	938.10	1185.01
G	Preference rank	SE, FE	0.10	0.08	434.67	550.55	890.10	1113.33	926.38	1136.58
H	Preference rank	TI, SE, FE	0.10	0.08	433.58	547.89	883.65	1110.1	912.79	1137.18

AICc: corrected Akaike information criterion; BIC: Bayesian information criterion.

Table 6. Significant predictors of ordinal regression models of preference rank for cluster N based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variable	Significant predictors[1]	Parameter estimate (β)	Standard error (SE)	*P*-value
A	Preference rank	TI	Taste intensity	-0.18	0.03	<0.001
B	Preference rank	SE	Disgusted	-0.72	0.11	<0.001
			Satisfied	0.25	0.09	0.009
C	Preference rank	FE	EV Disgust	-0.51	0.10	<0.001
			EV Contempt	0.50	0.15	<0.001
			EV Anger	0.41	0.14	0.003
			EV Sadness	-0.37	0.17	0.027
D	Preference rank	ANS	No significance			
E	Preference rank	TI, SE	Disgusted	-0.60	0.11	<0.001
			Good	0.33	0.14	0.016
			Taste intensity	-0.13	0.03	<0.001
F	Preference rank	TI, FE	EV Contempt	0.41	0.15	0.006
			EV Sadness	-0.41	0.17	0.013
			EV Disgust	-0.22	0.09	0.021
			Taste intensity	-0.16	0.03	<0.001
G	Preference rank	SE, FE	Disgusted	-0.65	0.11	<0.001
			EV Disgust	-0.57	0.12	<0.001
			Good	0.51	0.17	0.003
			EV Anger	0.47	0.15	0.002
			Free	-0.28	0.13	0.032
			EV Joy	0.16	0.06	0.012
H	Preference rank	TI, SE, FE	Disgusted	-0.56	0.11	<0.001
			EV Sadness	-0.44	0.16	0.005
			Good	0.33	0.14	0.013
			Taste intensity	-0.13	0.03	<0.001

EV represents an evidence value.

Table 7. Significant predictors of ordinal regression models of preference rank for cluster E based on taste intensity (TI), self-reported emotions (SE), facial expressions (FE), and autonomic nervous system responses (ANS)

Model code	Dependent variable	Independent variable	Significant predictors[1]	Parameter estimate (β)	Standard error (SE)	*P*-value
A	Preference rank	TI	Taste intensity	-0.14	0.02	<0.001
B	Preference rank	SE	Disgusted	-0.69	0.10	<0.001
			Satisfied	0.28	0.10	0.004
C	Preference rank	FE	EV Disgust	-0.32	0.09	<0.001
			EV Sadness	-0.29	0.13	0.024
D	Preference rank	ANS	No significance			
E	Preference rank	TI, SE	Disgusted	-0.61	0.10	<0.001
			Satisfied	0.27	0.10	0.006
			Taste intensity	-0.06	0.03	0.019
F	Preference rank	TI, FE	EV Disgust	-0.20	0.09	0.029
			Taste intensity	-0.12	0.02	<0.001
G	Preference rank	SE, FE	Disgusted	-0.69	0.10	<0.001
			Satisfied	0.28	0.10	0.004
H	Preference rank	TI, SE, FE	Disgusted	-0.61	0.10	<0.001
			Satisfied	0.27	0.10	0.006
			Taste intensity	-0.06	0.03	0.019

[1]EV represents an evidence value.

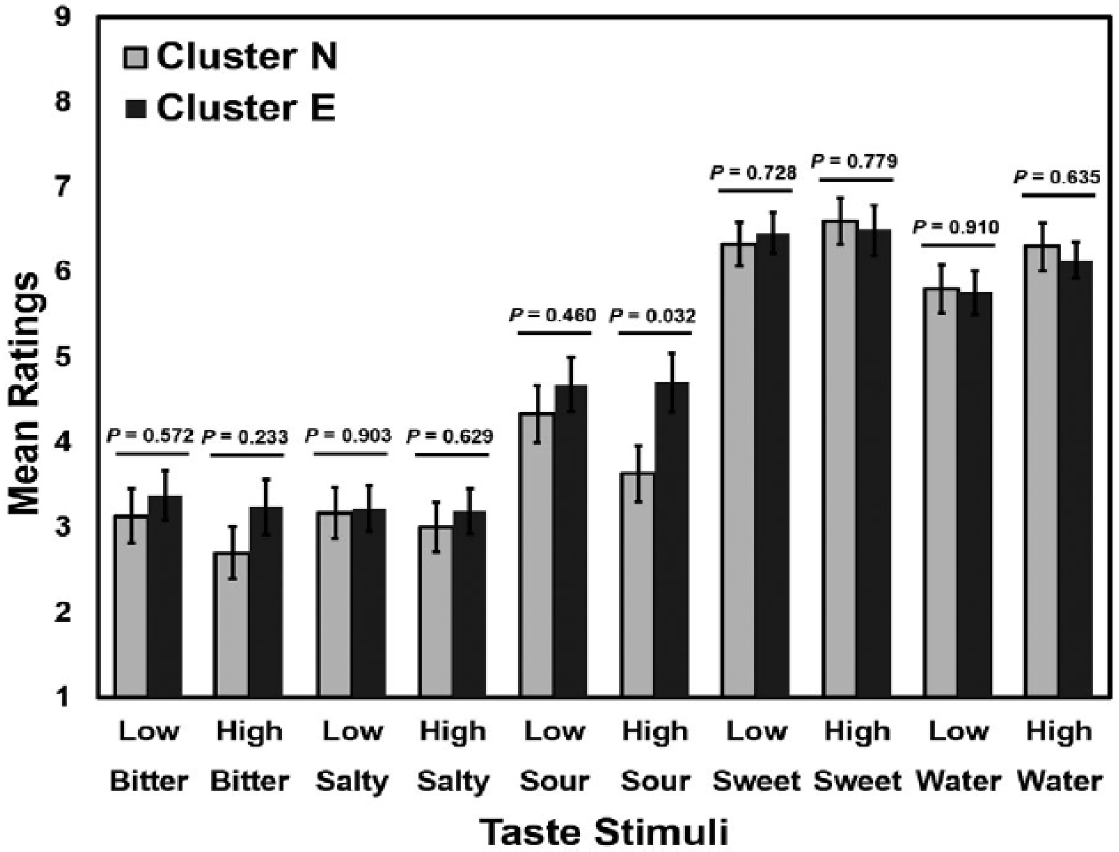
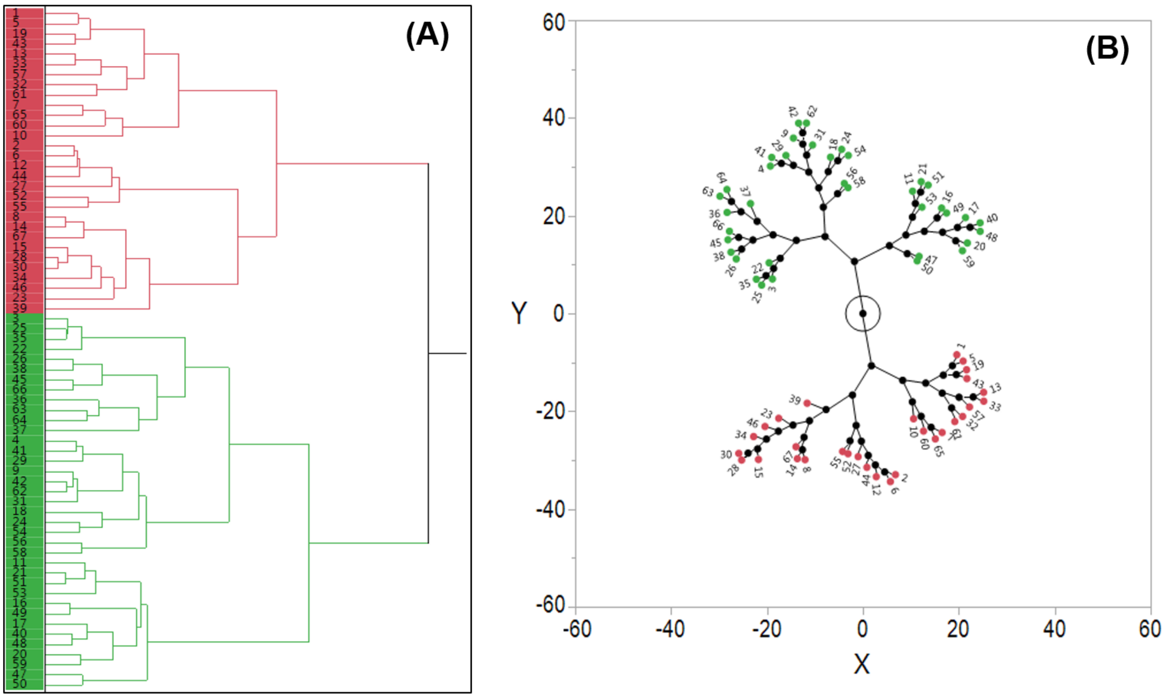


Figure 1. Mean comparisons between clusters N (high neuroticism) and E (high extraversion) with respect to overall liking of individual taste stimuli: basic taste solutions at low and high concentration levels and spring water. Overall liking of spring water sample was tested in both low and high concentration sessions of basic taste solutions.



Supplementary Figure 1: A dendrogram (A) and a constellation plot (B) drawn by a hierarchical cluster analysis using Ward's method for the personality traits measured by the Big Five Inventory (John et al., 1991). The length of horizontal lines between (sub) clusters reflects the relative distance between the clusters that were joined. The dendrogram shows that 67 participants could be classified into two clusters, cluster N (red) and cluster E (green), with the longest distance between the clusters. Such clustering without outliers could be observed in the constellation plot. The length of a line between cluster joins represents the distance between the clusters that were aggregated. Small numbers (from 1 to 67) in both (A) and (B) represent 67 participants in this study.

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CHAPTER 7

GENERAL CONCLUSION

To summarize, findings from Chapter 3 suggest that combination of self-reported emotions and facial expression analysis, along with taste sensory intensity perception works best to predict consumer acceptance and preference toward basic taste solutions. Chapters 4 and 5 extend these findings toward commercially-available beverages when tested under blind-tasting and informed-tasting conditions, respectively. In particular, Chapter 4 showed that combination of sensory attribute intensities, self-reported emotions, and facial expression analysis can best predict consumer acceptance of commercially-available vegetable juice samples when measured under blind-tasting conditions. However, overall variation explained by these prediction models for preference rank was low. In addition, Chapter 4 highlights the test-retest comparison of all measured variables. Next, Chapter 5 showed that the previous findings from basic taste models and blind-tasting condition models can be extended to predict purchase behavior. Specifically, Chapter 5 found that even though sensory attribute intensities and non-sensory factors such as brand and product familiarity are important predictors of purchase behavior, emotional responses provide additional valuable information to predict purchase intent and final choice among participants. Finally, Chapter 6 addresses some individual differences among consumers that might influence previously developed prediction models. Findings from this chapter suggest that prediction models of acceptance and preference among participants differed as a function of personality traits, especially high extraversion and high neuroticism traits. In conclusion, this dissertation study recommends the combined use of explicit (self-reported emotions) and implicit (facial expression analysis and autonomic nervous system responses) emotional measures, in addition to sensory and/or non-sensory cues, to predict consumer behavior in terms of acceptance, preference, and purchase-related decisions. To the best of authors knowledge, this is the first study to explore and compare the convergent validity of implicit and explicit methods used to measure food/beverage-evoked emotional responses. These findings can prompt sensory scientists, applied-emotion researchers, and food manufacturers to consider using a combination of explicit and implicit emotional responses to better understand consumer behavioral aspects such as acceptance, preference and purchase-related decisions as compared to individual variables.

APPENDIX 1

Research compliance protocol letters – Consent Forms

(A)

INFORMED CONSENT

Title: Emotional responses evoked by beverages

Researcher(s):
Han Seok Seo, Ph.D., Faculty
Tonya Tokar, Researcher
Shilpa Samant, Graduate student

University of Arkansas, CAFLS
Department of Food Science
2650 N. Young Avenue
Fayetteville, AR 72704
479-575-4778 (Seo)
hanseok@uark.edu (Seo); tpriesm@uark.edu (Tokar)
shilpa.samant15@gmail.com (Samant);

Administrator:
Ro Windwalker, CIP
IRB Coordinator
Office of Research Compliance
109 MLKG Building
University of Arkansas
Fayetteville, AR 72701
479-575-2208
irb@uark.edu

Description: This study aims to examine your emotional response to certain beverage samples. You will be asked to drink some beverage samples. After drinking the sample, you will rate emotions evoked by the beverage on the questionnaire provided. You will also rate intensity perceptions and overall liking of the beverage. During the study, sensors will be placed on your hands to measure small electrical changes in your skin, heart rate, and fingertip temperature. Additionally, your facial expressions during the study will be recorded using a web-camera. It takes about 40-45 minutes to complete this study.

Risks and Benefits: If needed, you will receive beverage samples. All beverage samples used in this study are commercially available. However, if you have known allergies or intolerances for specific foods or odors, please describe them here: ____.

After completing this study, you will get a Walmart gift card ($15) as reward.

Voluntary Participation: Your participation in the research is completely voluntary. The voluntary participation, i.e., choosing to participate or not, will have no effect on your relationship with the researchers or the University in any way.

Confidentiality: Your information on identity (e.g., name) will be coded as number (e.g., 1, 2, 3, etc.). The code number will be matched with your responses; In other words, your data including video data recorded during this study will be recorded anonymously. All information will be kept confidential to the extent allowed by law and University policy. Results from the research will be reported as aggregate data. The video data recorded during this study will be deleted after completion of journal publication.

Right to Withdraw: You are free to refuse to participate in the research and to withdraw from this study at any time. Your decision to withdraw will bring no negative consequences — no penalty to you.

Informed Consent: I, ____(please print), have read the description, including the purpose of the study, the procedures to be used, the potential risks, the confidentiality, as well as the option to withdraw from the study at any time. Each of these items has been explained to me by the investigator. The investigator has answered all of my questions regarding the study, and I believe I understand what is involved. My signature below indicates that I freely agree to participate in this study and that I have received a copy of this agreement from the investigator.

____

Signature **Date**

If you have questions or concerns about this study, please contact one of the researchers listed above. For questions or concerns about your rights as a research participant, please contact the University's IRB Coordinator listed as "Administrator" above.

IRB #16-06-814
Approved: 07/18/2016
Expires: 07/17/2017

(B)

INFORMED CONSENT

Title: Emotional responses evoked by beverages

Researcher(s):
Han Seok Seo, Ph.D., Faculty
Tonya Tokar, Researcher
Shilpa Samant, Graduate student

University of Arkansas, CAFLS
Department of Food Science
2650 N. Young Avenue
Fayetteville, AR 72704
479-575-4778 (Seo)
hanseok@uark.edu (Seo); tpriesm@uark.edu (Tokar)
shilpa.samant15@gmail.com (Samant);

Administrator:
Ro Windwalker, CIP
IRB Coordinator
Office of Research Compliance
109 MLKG Building
University of Arkansas
Fayetteville, AR 72701
479-575-2208
irb@uark.edu

Description: This study aims to examine your emotional response to certain beverage samples. You will be asked to drink some beverage samples. After drinking the sample, you will rate emotions evoked by the beverage on the questionnaire provided. You will also rate intensity perceptions and overall liking of the beverage. During the study, sensors will be placed on your hands to measure small electrical changes in your skin, heart rate, and fingertip temperature. Additionally, your facial expressions and/or temperature during the study will be recorded using a web-camera and a thermal camera, respectively. In addition, you will fill out questionnaires regarding personality traits. It takes 40-45 minutes to complete the study without EEG measurement.

Risks and Benefits: If needed, you will receive beverage samples. All beverage samples used in this study are commercially available. However, if you have known allergies or intolerances for specific foods or odors, please describe them here: ____.

After completing the sensory testing, you will get a Walmart gift card ($20) as a panel reward.

Voluntary Participation: Your participation in the research is completely voluntary. The voluntary participation, i.e., choosing to participate or not, will have no effect on your relationship with the researchers or the University in any way.

Confidentiality: Your information on identity (e.g., name) will be coded as number (e.g., 1, 2, 3, etc.). The code number will be matched with your responses; In other words, your data including video data recorded during this study will be recorded anonymously. All information will be kept confidential to the extent allowed by law and University policy. Results from the research will be reported as aggregate data. The video data recorded during this study will be deleted after completion of journal publication.

Right to Withdraw: You are free to refuse to participate in the research and to withdraw from this study at any time. Your decision to withdraw will bring no negative consequences — no penalty to you.

Informed Consent: I, ____(please print), have read the description, including the purpose of the study, the procedures to be used, the potential risks, the confidentiality, as well as the option to withdraw from the study at any time. Each of these items has been explained to me by the investigator. The investigator has answered all of my questions regarding the study, and I believe I understand what is involved. My signature below indicates that I freely agree to participate in this study and that I have received a copy of this agreement from the investigator.

____

Signature **Date**

If you have questions or concerns about this study, please contact one of the researchers listed above. For questions or concerns about your rights as a research participant, please contact the University's IRB Coordinator listed as "Administrator" above.