chemosensors

Review

E-Senses, Panel Tests and Wearable Sensors: A Teamwork for Food Quality Assessment and Prediction of Consumer's Choices

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Abstract: At present, food quality is of utmost importance, not only to comply with commercial regulations, but also to meet the expectations of consumers; this aspect includes sensory features capable of triggering emotions through the citizen's perception. To date, key parameters for food quality assessment have been sought through analytical methods alone or in combination with a panel test, but the evaluation of panelists' reactions via psychophysiological markers is now becoming increasingly popular. As such, the present review investigates recent applications of traditional and novel methods to the specific field. These include electronic senses (e-nose, e-tongue, and e-eye), sensory analysis, and wearables for emotion recognition. Given the advantages and limitations highlighted throughout the review for each approach (both traditional and innovative ones), it was possible to conclude that a synergy between traditional and innovative approaches could be the best way to optimally manage the trade-off between the accuracy of the information and feasibility of the investigation. This evidence could help in better planning future investigations in the field of food sciences, providing more reliable, objective, and unbiased results, but it also has important implications in the field of neuromarketing related to edible compounds.

Keywords: chemosensory analysis; e-senses; emotions; food choice; neuromarketing; wearables; panel test

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1. Introduction

Nowadays, the monitoring of food to ensure an acceptable level of quality and safety is still pivotal [1], particularly when considering the growing consumers' requests for safe and high-quality food; traits that influence the price that consumers are willing to pay. Therefore, food industries must be sure to meet consumers' expectations to be effectively competitive in the market. Furthermore, it has been demonstrated that the sensory features of the products, such as color, shape, flavor, and taste, play important roles in the consumer's perception and are therefore primary drivers for the acceptability of the food products [2]. For instance, specific sensory traits, including excessive bitterness or acidity, presence of off-flavor, or color changes due to reduced freshness, may constitute a barrier to the consumption of food products [2]. The quality is generally described in relation to nutritional, microbiological, and physicochemical characteristics, but none of these parameters serve as a fully comprehensive descriptor of quality. These parameters can be analyzed by traditional analytical approaches; however, the precise quantification of specific compounds inside a product does not always reflect the final perception returned by the human senses. Therefore, another technique applied to assess the quality from a consumer point of view is represented by sensory analysis [3], which is based on the evaluation of the products through the five sense organs [4].

According to this view, there is a tradition in food sensory science in which the sensory features measured are considered as properties of the food itself [5]. While attributing sensory properties to the food rather than the person was meant to be a convenient way of conceptualizing those aspects of the food perception being measured [5], this widespread approach has consequences on the knowledge of human–food interactions.

Generally speaking, during both panel tests or a generic tasting experience, in higher-order brain areas, all the food's sensory attributes combine together with the context (environmental, social and cultural contexts, individual traits, etc.) to produce a global representation of their sensory experience. The total information is elaborated in order to create a decision-making process [6,7]. The perceived quality as well as the desirability of foods and beverages mainly rely on signals other than the food itself, such as cultural background and social environment, together with emotions and memories from past experiences. Furthermore, according to Plassman and co-workers [8], any action capable of creating expectations about product quality would be able to modulate experienced pleasantness.

In this context, while it is widely accepted that emotions are a cardinal step in sensory evaluation and are associated with how consumers make purchase decisions or give preference for specific foodstuffs, it is still far to be understood if, when, and how emotions should be used as a strategy to evaluate food quality and preference [9]. Perceptual theories posit that emotions carry important information about the world and that "they inform us about our internal physiological and psychological reactions to external events and situations" [10] (see [11] for discussion), thus stimuli—such as food flavor—are firstly capable of activating internal processes in the body, and the signals evoked can be further detected and/or quantified. As such, in order to investigate the processes underlying emotions in humans, different approaches and instruments are employed. Such instruments are capable of detecting either explicit or implicit methods. As such, explicit methods, more widely used until recently, include verbal or visual, self-reported procedures, or asking individuals to report their feelings faced with a given scenario or product. Although quick, affordable, and easy to administer, explicit methods can be affected by cognitive biases, making their use always more debated [12]. In this scenario, implicit methods gained importance, fostered by the continuous advances in Information and Communication Technologies. Indeed, they make use of indirect, non-self-reported measures to continuously register emotions during a given action, including while smelling, eating, or looking at food. Usually, they rely on several kinds of biological responses, including cerebral, cardiovascular, electrodermal, respiratory, and other responses.

Taken together, experimental evidence allows us to conclude that the only way to try to understand the basic principles related to both food's sensory characterization and consumer's behavior in terms of food choice, is to apply a multidisciplinary approach in which Sensory sciences, Food technology, and Information and Communication Technologies, particularly those relying on Bioengineering principles, are considered as complementary tools to describe the same cognitive process.

In this context, a critical review of recent literature about the three above-mentioned main topics was provided to highlight the main issues related to food quality assessment also in order to predict consumers' food choices. Furthermore, the question of "if/when/how it's possible to manage the role of emotions on trained panel performances and consumer's behavior" was also addressed.

To improve the clarity, the entire manuscript has been divided into three main sections: (a) Food technology—e-senses to measure main chemical/physical features of food; (b) Sensory analysis—direct interaction human/food and explicit methods to measure emotions during tasting; and (c) Bioengineering—implicit methods to measure emotions during the tasting. According to Figure 1, the three sections cannot be classified into different hierarchical levels as they address distinct aspects of the same overall picture.

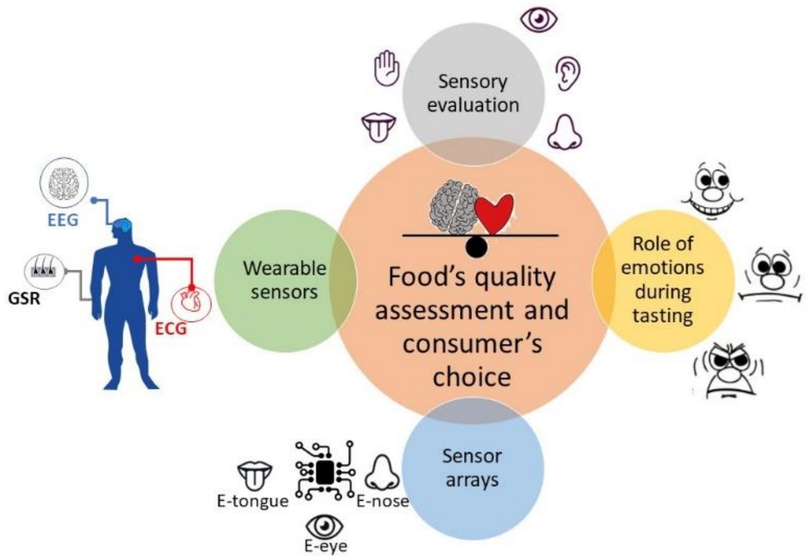

Figure 1. Summary diagram.

2. Review Methodology

To provide the highest coverage for relevant papers published between January 2016 and April 2022, the main electronic bibliographic databases (e.g., Web of Science, ScienceDirect, and PubMed) were consulted. Only the last six years were considered due to the recent improvements in technology solutions and methods of sensory assessment. Initially, authors focused their attention on the available reviews, in order to critically select the main documents recently published on the topic. Then, older literature sources suitable to improve and widen the topic description were also included, starting from the literature of the documents selected in the predetermined time period. By means of predefined eligibility criteria, the available papers were evaluated independently by six investigators (two for each sub-topic). Any disagreement was addressed and resolved when necessary by discussion during a consensus panel including all the six investigators involved in the selection. For each sub-topic (Food technology—e-senses to measure main chemical/physical features of food; Sensory analysis—direct interaction human/food and explicit methods to measure emotions during tasting; and Bioengineering—implicit methods to measure emotions during tasting) the first inclusion criterion was represented by the relevance of the topic to our discussion about the specific state of the art. In the case of papers dealing with the effect of different factors, we utilized hierarchic approaches to opt for the fitting sections of discussion.

3. Food Technology—E-Senses to Measure Main Chemical/Physical Features of Food

In food quality assessment, the sensory approach gives an immediate measurement of perceived attributes and returns information, which helps to better understand human responses. However, sensory analysis is often time-consuming and expensive, and the training of the sensory panelist can be tricky. Therefore, research has focused for a long time on how to substitute human sensory organs with artificial senses (electronic nose, tongue, and eye), which are innovative devices based on chemical and physical sensors able to mimic the complex mechanisms of human senses [13]. E-senses have been used to characterize food features associated with sensory and compositional profiles, in a rapid and objective way. The use of E-senses for food quality evaluation has recently been reviewed many times [1,14,15]. This section focuses on the recent applications of E-senses for food evaluation, especially considering traits that influence humans' perception of food quality.

3.1. E-Nose

An electronic nose (E-nose) is a tool that works through a series of sensors able to detect volatile organic compounds (VOCs) in different types of samples. It is composed of three main parts: sample delivery system, chemical sensors, and pattern recognition system [16]. Gas sensors can be classified into different types, based on the materials: conducting polymers (CP), metal-oxide semiconductors (MOS), metal-oxide semiconductor field-effect transistors (MOSFET), and mass-sensitive (such as quartz microbalance), and acoustic and optical sensors [16,17]. The VOCs emitted by the samples react with the sensors, causing reversible electrical signals, which are properly analyzed to extrapolate a possible pattern of some significance for the given analysis [17]. The intensity of the sensor's signal depends on specific parameters, such as the nature of the VOC (type and concentration), reaction between VOCs and sensors, type of sensor, and environmental and sampling conditions [16]. After the processing, what is obtained is an aromatic fingerprint. The E-nose can be trained to interpret the results differentially depending on the food industry needs, and the sensors can be customized based on the desired application [15]. As being able to mimic the human smell, the E-nose has been largely tested in the food industry to identify specific aromatic fingerprints associated with food quality, especially considering that different aspects influence the intensity and composition of food aroma profile. Hence, the food aroma plays a crucial role in assessing food quality and internal composition, as well as consumers' expectations. Consequently, the aromatic evaluation has become part and parcel of the food production process for quality inspection purposes [18]. An e-nose finds application in different steps of the agri-food production chain, such as ripening stages and harvesting time evaluation, storage conditions, and shelf-life evaluation, including the assessment of freshness or decay degree, microbial contamination, and off-flavor formation [17]. This appears particularly important considering that food pathogens and off-flavor production can lead to important economic loss and consumer rejection. For instance, Viejo et al. [19] proposed an integrated artificial intelligence system to detect off-flavors in beer using a low-cost, portable e-nose coupled with machine learning modeling. The Authors were able to build three highly accurate models able to predict beer faults with 95, 96, and 97% accuracy. Moreover, Fuentes and colleagues [20] evaluated the potential of a low-cost e-nose to assess the smoke-taint fault in wines. Using the e-nose measurements as input in the machine learning model, it was possible to assess the number of smoke-related compounds in wines, such as 20 glycoconjugates and 10 volatile phenols with high accuracy (with R2 ranging from 0.95 to 0.99). Some examples of e-nose applications for food quality evaluation are shown in Table 1. The e-nose shows to be a rapid, reliable, and low-cost technology to assess food and beverages quality [21]. Moreover, the e-noses can be installed at different production stages for quality monitoring during the whole production process, which can help in taking fast corrective actions before obtaining the final product [22]. Besides the considerable advantages of the e-noses, there is still a great difference with the human olfactory system. Hence, the technological approach has a certain type of limitation due to sensor structure and analytical methods. For instance, sensor poisoning, calibration, and sensitivity can represent important drawbacks [18]. Additionally, even though the analysis is cheap and fast, a large number of samples is often required. Gas sensors are very sensitive to external environmental conditions, especially to temperature, humidity, and pressure. Therefore, an external condition during sampling strongly affects the response of the sensor. As such, controlled conditions are required during the analysis, which makes it difficult to use E-noses in outdoor settings [17]. Considering the obvious limitations of the e-nose systems, a valuable approach to make key decisions in the food production chain could be the combination of e-nose with sensory analysis approaches discussed above. In this sense, it would make it possible to combine the ability of the e-nose to perceive chemical compounds with the ability of the human nose to perceive the synergic interaction of chemical compounds mixture. Moreover, the combined use of e- and human senses would reduce the necessary resources (in terms of times and samples) of both approaches [3,16–18].

Table 1. Examples of E-Nose application for Food Analysis. MOS: metal-oxide semiconductors. ANN: artificial neural network; CDA: Critical discourse analysis; CT classification and regression tree; HCA: hierarchical cluster analysis; LDA: linear discriminant analysis; MARS: multivariate adaptive regression splines; PCA: principal component analysis; PLS: and partial least square; RBFNNs: radial basis function neural networks; SVM: support vector machine; SNV: standard normal variate.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Rice	Detection of fungal infection during storage	MOS	PCA, LDA, and PLS	[23]
	Peach	Fruit decay	MOS	PLS and SVM	[24]
	Apple	Detection of pathogen contamination	MOS	PCA and HCA	[25]
	Dragon fruit, pear, kiwi fruit, apple	Fruit deterioration	MOS	PCA	[26]
	Potato	Soft-rot infection	MOS	LDA, MARS, CT	[27]
	Broccoli	Freshness evaluation	MOS	PCA, HCA, CDA	[28]
	Citrus	Early detection of *Bactrocera dorsalis* infection	MOS	PCA and LDA	[29]
	Bell pepper	Freshness	MOS	PCA and PLS	[30]
	Mushrooms	Early detection of contamination	MOS	PCA and PLS	[31]
	Apple	Detection of pathogens (Salmonella, Erwinia, Streptococcus, and Staphylococcus) contamination	MOS	PCA and HCA	[25]
	Grapes	Identification of smoke-related volatiles	MOS	PCA	[32]
Oils and Dairy products	Olive oil	Evaluation of rancidity and oxidation	MOS	PCA and LDA	[33]
	Olive oil	Presence of defects	MOS	PCA	[34]
	Peony seed oil	Adulteration	MOS	PCA and LDA	[35]
	Edible oils	Adulteration	MOS	HCA, PCA, PCR, LDA, and ANN	[36]
	Parmigiano Reggiano cheese	Adulteration	MOS	PLS and ANN	[37]
	Butter	Adulteration	MOS	PCA and ANN	[38]
Meat and fish	Fish	Spoilage monitoring	MOS	-	[39]
	Tuna	Process development	MOS	PCA	[40]
	Salmon	Freshness evaluation during storage	MOS	RBFNNs and PCA	[41]
	Squid	Formaldehyde identification	MOS	PLS	[42]
Processed food	Grape syrup	Adulteration	MOS	PCA, HCA, SVM, and LDA	[43]
	Tomato paste	Adulteration	MOS	PCA, PLS, SVM, and LDA	[44]
	Chicken	Evaluation of roasted chicken deterioration	MOS	PCA	[45]
Beverages	Vinegar	Classification	MOS	PCA, SNV, and LDA	[46]
	Orange juice	Adulteration	MOS	HCA, ANN, and CT	[47]
	Beer	Off-flavor identification	MOS	ANN	[48]
	Wine	Smoke taint evaluation	MOS	ANN	[20]

3.2. E-Tongue

The human sense of taste involves identifying basic flavors, namely, sweetness, acidity, bitterness, salinity, and umami. Many researchers have introduced the electronic tongue (E-tongue) as a rapid and objective method to replace the human tongue [1]. The e-tongue is the analytical device based on the principles of functioning of the human sense of taste able to classify the tastes of various chemical compounds in liquid phase samples. Like the e-nose system, it allows the identification, classification, and analysis (both qualitative and quantitative) of the multicomponent mixtures, returning a taste fingerprint. Overall, it is based on a multi-channel taste sensor, composed of three parts: a sample-dispensing chamber, a sensory array with different selectivity, and software for data processing. The interaction between the sensors and the analytes gives a primary chemical energy output, which is a function of components' structure and concentration, and it is transformed into electrical output [49]. These measurable electrical signals are used to recognize and classify the pattern. Most of the e-tongue instruments are based on electrochemical techniques, namely, conductometry, voltammetry, and potentiometry [50]; the latter representing the most common and versatile one. These sensors are able to measure a great number of different compounds in different solutions. In several studies, voltammetric e-tongues have been used to identify sweeteners and acids (such as glucose, lactate, sucrose, lactic, and acetic acid) in different food products. In the agri-food sector, potentiometric sensors have been used to classify beers and wines [51]. Specifically, the e-tongue, based on potentiometric electrodes sensitive to sodium, calcium, ammonia, and anion was able to discriminate 34 types of beers from different brands and types. Moreover, it was able to discriminate the presence of stabilizers and antioxidants, unmalted cereals, and carbohydrates added during fermentation. The same system was used to analyze wines and was able to discriminate the different wines based on the varieties used for the winemaking (Chardonnay, Americanas, Malbec, and Merlot). In Table 2 are reported some examples of e-tongues used for food analysis.

Table 2. Examples of E-tongue application for Food Analysis. ANN: artificial neural network; CDA: Critical discourse analysis; CT classification and regression tree; ELM: extreme learning machine; HCA: hierarchical cluster analysis; LDA: linear discriminant analysis; MARS: multivariate adaptive regression splines; PCA: principal component analysis; PLS: and partial least square; RA: regressive analysis; RBFNNs: radial basis function neural networks; SNV: standard normal variate; SVM: support vector machine.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Coffee beans	Evaluation of bitterness	Potentiometric	RA	[52]
	Melon	Evaluation of storage condition	Potentiometric	PLS and LDA	[53]
	Corn seeds	Aflatoxin detection	Potentiometric	PLS	[54]
Oils and Dairy products	Vegetable oil	Adulteration with low-grade oils	Solid-state electrodes	RA	[55]
	Olive oil	Rancidity evaluation	Potentiometric	LDA	[56]
	Milk	Discrimination based on storage days	Voltammetric	ANN	[57]
	Paneer cheese	Evaluation of capsaicin content	Potentiometric	PCA	[58]

Table 2. *Cont.*

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Meat and fish	Fish	Presence of heavy metals	Colorimetric	PLS and ELM	[59]
	Mutton	Adulteration with pork or chicken meat	Potentiometric	PCA, LDA, CDA, and BAD	[60]
	Fish	Freshness evaluation during storage	Potentiometric	PCA-RBFNNs	[61]
	Carp	Evaluation of flavor changes during steam cooking	Potentiometric	PCA	[62]
Processed products	Tomato soup	Comparison of consumer perception and e-tongue of different salts	Potentiometric	PCA	[63]
	Soy sauce	Identification of rare sugars	Potentiometric	PCA	[64]
	Surimi	Flavor after different processing methods	Potentiometric	PCA	[65]
Beverages	Wine	Evaluation of phenols content	Voltammetric	PLS	[66]
	Wine	Adulteration of tokaj	Potentiometric	PCA, LDA, and PLS	[67]
	Wine	Off-flavor identification	Potentiometric	PCA	[68]
	Apple juice	Evaluation of sweetness	Impedance spectroscopy	PCA	[69]
	Liquor	Comparison of human perception and e-tongue in differentiating liquors	Potentiometric	PCA	[70]
	Coconut water	Taste deterioration during time	Potentiometric	PCA	[71]

As such, the e-tongue represents a powerful tool to characterize sensory properties of different food products; however, like the e-nose, it still has some important limitations. One of the main disadvantages of e-tongue sensors is that they can be sensitive to temperature and, therefore, sensors' temperature control is often required. Furthermore, the sensors are often characterized by a relatively short lifespan and a frequent and careful check of e-tongue performance and reliability is pivotal; in this case, a large number of samples is also required to have a solid and reliable result [15]. Lastly, considering that human taste also perceives astringency, viscosity, heat, spicy, and so on, a complete description of the overall taste with the e-tongue alone is not possible. Again, and even more important than in the case of the e-nose, the combined approach of e- and human tongue would bypass these limitations.

3.3. E-Eye

Contrary to smell and taste, visual perception is not a chemical sense. Eye photoreceptors are capable of reacting to light and, therefore, collecting information from the external environment, which will be transformed into electrical signals. In this sense, this section may sound inconsistent with the other topics presented in the review. However, it must be highlighted that the visual appearance of food products is a critical aspect of consumers' quality expectations, and it plays a crucial role in the decision to purchase—or consume—or not a specific product. Appearance, color, lightness, and texture are the first sensory factors that the consumers perceive, and they determine products' success. As such, careful and reliable monitoring of food visual traits is crucial and cannot be ignored [72]. In this context, the electronic eye (E-eye) has proven to give a fast, accurate, and cheap evaluation of food shape, size, color, lightness, morphology, and texture. Moreover, it can measure changes in appearance over time at each step of the production chain [73]. The e-eye system is based on different elements: light source, camera (in the case of an analog camera, a frame grabber to convert the analog to a digital signal is necessary), computer with software, and high-resolution monitor. As for the human eye, the main factors influencing the operation of vision are the intensity and the type of light. As such, properly designed lights should be considered in order to improve the precision and reliability of the analysis [74]. Generally, the most used light sources include fluorescent and incandescent bulbs, but also LED, quartz halogen, metal halide, and high-pressure sodium lamps are quite popular. The lamp system can be arranged in a circular layout, which is used for flat samples, or scattered layout, used for round-shaped products. The other crucial component of the system is the camera (analog or digital), which is needed to record the image of the samples that are then sent to the computer [73]. Analysis with e-eye is fast and extremely easy: it is non-destructive, it does not require sample preparation and it allows multiple samples and different parameters (i.e., color and shape) in just one run [75]. Among the multiple applications, the e-eye is widespread in the food industry: it is used for the classification of fruits and vegetables, to monitor specific production processes such as aging, fermentation, or roasting, to detect defects and imperfections, and to verify color changes during food storage or processing [76]. Hence, color is strictly linked with food freshness evaluation, especially in perishable food products or with processed food quality. For instance, the maturity level of grapes strongly influences the quality traits of the resulting wines. Among the different parameters generally used to monitor the ripening, such as sugar and acidity, polyphenol content plays a crucial role in the color, structure, astringency, and body of the final wine. As such, Orlandi and colleagues [77] tested an e-eye to predict the ripening stages of wine grapes based on their polyphenol content. With e-eye output and modeling approaches, the system was able to predict some important parameters related to grape phenolic ripening, such as color index, tonality, anthocyanins content, and specifically, malvidin-3-O-glucoside and petunidin-3-O-glucoside. The visual parameters detected with the e-eye allow the exclusion of faulty, substandard, or deteriorated products. Some proposed applications are summarized in Table 3. However, an important point is that poor and inadequate working conditions, such as scarce illumination, can dramatically change the quality of the images, therefore returning unreliable information. Additionally, the characteristic of the sample surface can scatter or reflect the light and, consequently, the quality of the image. As such, an accurate choice of light sources and intensity based on the environmental conditions and food properties is crucial to obtaining satisfactory results.

Table 3. Examples of E-Eye application for Food Analysis. CCD: Charge-Coupled Device; NIR: near-infrared; CMOS: complementary metal-oxide semiconductor. ANN: artificial neural network; CNN: convolutional neural networks; DFA: discriminant factor analysis; PCA: principal component analysis; PLS: and partial least square; RA: regressive analysis; RF: random forest; SVM: support vector machine; RA: regressive analysis; RF: random forest.

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Agri food	Wine grapes	Color changes during ripening	Colorimetric	PLS and PCA	[77]
	Climacteric fruits	Identification of artificially ripened fruits	Colorimetric	CNN	[78]
	Corni Fructus	Discrimination based on color graduation	Colorimetric	DA, PCA, PLS, SVM, and DA	[79]
	Tomato	Quality monitoring during storage	CCD camera	PLS	[80]
	Strawberries	Evaluation of Fungal Contamination	Vis–NIR hyperspectral imaging system	-	[81]

Table 3. *Cont.*

Food Category	Sample	Application	Sensor	Chemometric Approach	Reference
Oils and Dairy products	Citrus oil	Measure the color difference	Colorimetric	DFA	[82]
	Olive oil	Characterization	Colorimetric	PCA	[13]
Meat and fish	Meat	Freshness evaluation	Vis–NIR hyperspectral imaging system	PLS	[83]
Processed products	Dried tangerine peel	Quality evaluation after different processing methods	Colorimetric	DFA	[84]
	Carasau Bread	Monitoring manufacturing process	Colorimetric	ANN	[85]
Beverages	Tea	Quality evaluation	CMOS camera	PLS, SVM, and RF	[86]

4. Sensory Science—Direct Interaction Human/Food and Explicit Methods to Measure Emotions during Tasting

Generally speaking, during a panel test, the data collected by the five senses of trained judges (sight, touch, smell, taste, and hearing) can be interpreted and statistically analyzed to fully characterize a food product during the whole production process as well as during storage. As previously reported [87–91], over the last decades, this analytical approach has been suitably applied alone or in combination with specific e-senses [17] in the Food technology field for several main purposes, such as the development of new processes and/or products, quality control, consumer acceptability, flavor, and taste characterization, etc.

To improve the reliability of sensory results as well as to manage the main possible biases derived from external conditioning, new official methods for sensory analysis of specific categories of products have been developed and validated over time. However, in spite of such efforts, the possibility to reliably predict food choice or purchase behavior still appears far to be achieved [92]. Liking the sensory properties of a food's appearance, indeed, is mandatory, but not sufficient to explain food choice [93]. As a consequence, nowadays, sensory laboratory tests or consumer trials are excellent at rejecting bad products, but not very efficient at predicting which acceptable products will still maintain their appeal in 5 years' time [94]. There are many reasons for this failure, which has persisted even as research has become more sophisticated by taking into consideration the complex context in which food choice occurs [95–97].

To solve this gap, the past decade has seen a dramatic increase in interest toward the evaluation of emotions in consumer and sensory science [12,98]. In particular, valence (degree to which an emotion is favorable or negative) is at the core of the current hedonic measures in sensory science (under the assumption that good products provide pleasure). In addition, while the measurement of the arousal (intensity, or the power of the accompanying emotional state) is not always routine, it is nevertheless a key variable underlying the impact of stimulus complexity on hedonic responses [99]. Therefore, to deepen our understanding about the role of emotions in shaping perceived food quality, it seems of utmost importance to use a combination of explicit methods (self-reported ratings) to measure "valence" and implicit methods (measurement of physiological reactions) to better evaluate "arousal" [9].

In this context, the recent research outlined above strongly points to the importance of a variety of factors that need to be considered when the measure of emotions is addressed in food-related studies, involving both trained judges and consumers [94]. Among others, in the following subsections of this paragraph, the importance of the development of an emotion lexicon specific for each foodstuff to be characterized, the influence of the context in which the tasting occurs, as well as the role played by the main features determining the taster's attitudes toward foods, will be addressed and discussed. The main issues affecting the performances of trained panelists will also be considered.

4.1. Emotion Lexicon

As widely reported in the literature [9–12], emotions have been defined as a patterned collection of chemical and neuronal responses that are produced by the brain when it detects the presence of an emotionally competent stimulus, such as an object or situation. Perceptual theories posit that emotions carry important information about the world and that "they inform us about our internal physiological and psychological reactions to external events and situations". In other words, emotions can be defined as physical signals of the body reacting to external stimuli.

According to Pedroza and collaborators [9], in a recent review in the specific context of wine consumption, the interest in characterizing emotions elicited by external stimuli strives from the evidence that they have been linked to affective behavior and decision making involving mood, motivation, drive, desire, preference, attitude, passion, and arousal [11,100]. In addition, three postulates can be stated [11]: (i) evolution has played an important role in shaping emotions features and function, (ii) they differ significantly from one another, and (iii) basic emotions can be blended to obtain non-basic ones.

In this context, creating specific lexicons adapted for different populations is at the base of the development of explicit methods to measure the emotions elicited by food. Concerning wine, for example, after the crucial work of Ferrarini et al. [101], four further studies have proposed the wine emotion lexicon [102–105], based on different methodological approaches and, remarkably, including the tasting of real wine samples. Figure 2 presents a compilation of the 72 unique terms (not repeated) used to describe emotions evoked by wine from these studies as reviewed by Pedroza et al. [9]. Neutral/ambiguous terms were arbitrarily classified by the authors.

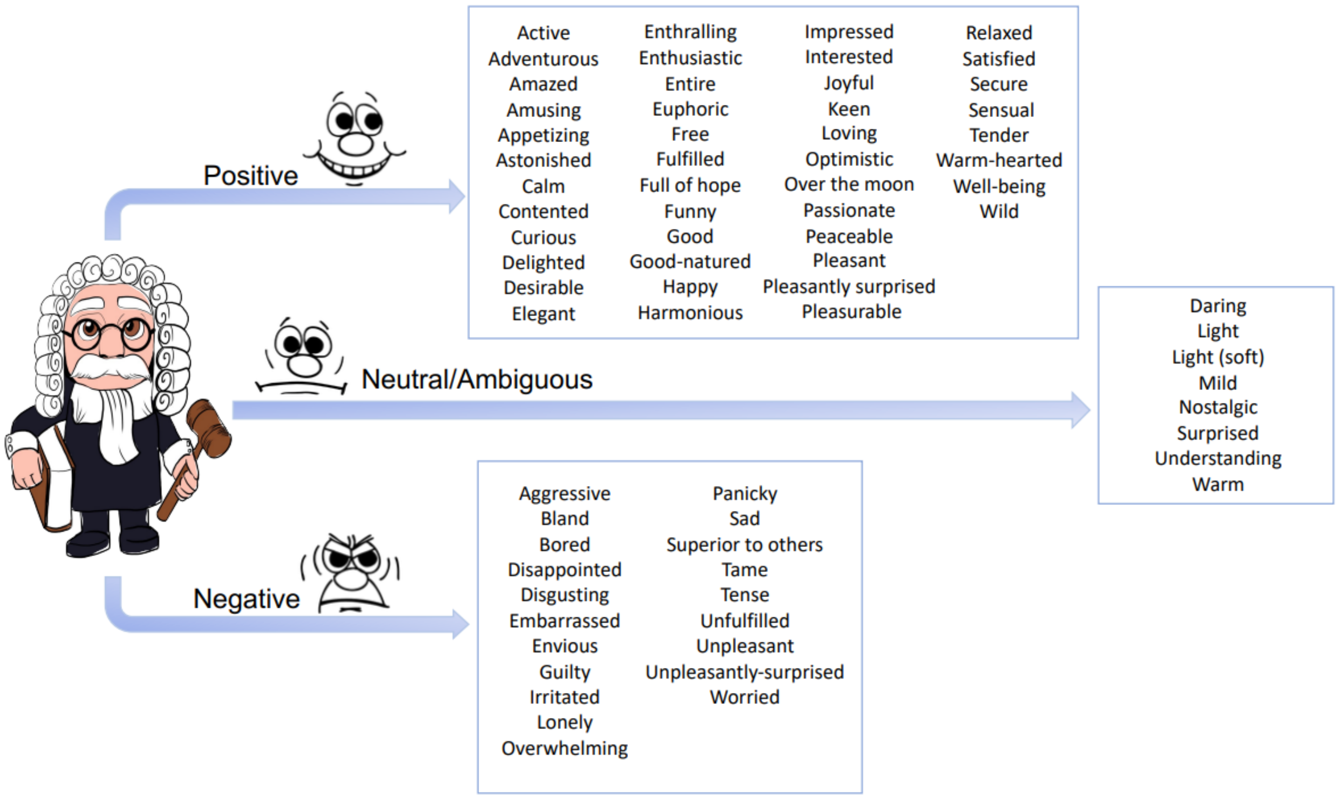

Figure 2. An example of Emotion lexicon evoked by wine. Data from [9].

4.2. Context

Context plays a key role in sensory and consumer science, as in any evaluation of a product, everyone provides their own experience, along with its emotional aspects [94]. Using structural equation modeling, Calvo-Porral et al. [106] deduced that the "occasion of consumption contributes to modify and shape the emotional experience in product consumption". Regarding emotions aroused by wine, Ristic and colleagues [107] defined a link between consumption occasion and sensory descriptors. Consuming wine in restaurants or in social environments, indeed, turned out to produce better positive emotions in comparison with the same evaluation performed in a laboratory testing context [108]. Moreover, Silva and colleagues [109] highlighted the preference for consuming wine with meals at home, parties, restaurants, and together with family and friends. The question to be answered from these findings then seems to be how to separate the contribution of context to experienced emotions. In this sense, Sinesio and co-authors [110] found that context, more than wine, influenced the rating of emotions and sensory terms.

4.3. Taster Profile

As with any other measurement in consumer research and sensory analysis, the measuring of emotion is affected by individual differences, which contribute to a large extent to the variance. According to Calvo-Porral and colleagues [102], in the specific and emblematic case of wine consumption, "the average consumer does not exist" and consumer groups could be hypothetically distinguished according to emotional descriptors aroused by tasting wines. Different product involvement analysis is then characterized by the classification of participants according to the frequency of wine consumption, and the knowledge and the appreciation of wine [102,103,106,108,111].

Some people discriminate between different emotional states in a more detailed way than others (granularity), and this appears to go beyond having a richer emotional vocabulary. As a fundamental consequence of variations in granularity in the use of emotion profiles, the choice of a small or large number of emotion words (EWs) will depend not necessarily on differences in response to a food, but on this characteristic of the cognition of an individual [94].

As the outcome of the numerous evidence showing that language modifies both our own expression of emotions and their interpretation by others, facilitating also the discrimination of emotions in cases of a higher ability to use emotional languages, taster profiling involves language ability as well as the level of education and other relevant indicators of socio-economic status that are justified in emotion studies. Moreover, not only context is needed to correctly identify expressions of so-called basic emotions, but also a reliable one-to-one relationship between a given expression and an internal feeling cannot be identified [94].

Finally, according to recent studies, even the determinants of individual differences in emotional responses to odors, culture, gender, and ability to accurately label, resulted in all being influential factors, depending on the emotion evaluated [94,112].

4.4. The Specific Case of Trained Panelist

A significant gap in the literature exists between the methods used to measure sensory attributes in consumers and professionals; consumer methods seem to rely primarily on liking or hedonic ratings, which precludes understanding of the sensory attributes behind it, while expert methods generally focus on descriptive attributes, disregarding or minimizing the subjective nature of hedonic judgments. On the other hand, trained panelists provide a description of the food, granting that the individual perception contributing to the information given is, to the greatest extent possible, suppressed as a consequence of the training [113], in an effort to capture direct sensory effects. According to a traditional model of food sensory science, consumers' decisions are assumed to be based on information that comes from the environment into their bodies. In this context, food scientists might assume that the influence of thinking processes on sensory evaluation could not be considered, focusing on “bottom-up” (stimulus-dependent) techniques, such as scaling and triangle tests, for the evaluation of taste, smell, and flavor [114]. This kind of evaluation is largely employed for the characterization of mean sensory aspects of a food for a given observation group (i.e., culture or age group). These techniques successfully permit to explain the basic processing of sensory analysis, such as how genetic variations could influence the perception of sweetness or bitterness, but as a consequence, little or no regard has been paid to higher cognitive processes—attention, learning, metacognition, language, and memory—which are integral components of the process of perception. In this context, the emotions eventually elicited by the trained panelists during the tasting are not generally considered as part of the process. This emphasis on bottom-up processes is due to the origin of the food science/marketing tradition of sensory science, focused on product, while the study of perception and cognition is strongly ingrained in psychology. According to this latter tradition, perception is intrinsically a consequence of “higher” mental processes, in that sensory information is shaped by cognitive processes, such as those involving past experiences, memories, and the subsequent expectations [115]. Therefore, from the role of “top-down” (model-dependent) influences [114] in the processing of food, such as information from other sensory systems or expectations based on prior experiences, food sensory science might raise new awareness about consumer behavior [5].

Classic wine tasting protocols, usually those practiced in wine-tasting rooms and used by professionals, include a sequence evaluation of olfactory, visual, taste, and mouthfeel attributes rated using scales. Nevertheless, including emotional attributes in this process could permit our understanding of fine wine quality to be extended [115]. In this sense, some authors have even started embedding emotional terms in tasting protocols from the International Organization of Vine and Wine [116]. Malfeito-Ferreira et al. [115] showed that wine appraisal begins with the olfactory attributes (nose), then the “Initial impression” and “expectations for the mouth” occur as emotional features. Secondarily, the mouth produces the attribute “Relation to smell”, in order to catch the congruence of expectations related to nose features. Finally, an overall emotional trait rating wines by means of a valence scale ranking from disagreeable to exciting is needed. Authors considered these expectations and congruence as part of the emotional traits of wine. Although the connection between emotions and sensory expectations/consistency needs a deeper explanation, the concept of integrating emotional features into conventional tasting procedures can innovatively improve our knowledge of hedonic processes in tasters.

5. Bioengineering—Implicit Methods to Measure Emotions during Tasting

In recent times, emotions have grown in popularity within scientific research related to marketing in order to capture the consumer’s wishes and interests. Implicit methods, making use of indirect, non-self-reported measures, has gained importance, fostered by the continuous advances in Information and Communication Technologies. Usually, they rely on several kinds of biological responses, including cerebral, cardiovascular, electrodermal, respiratory, and other responses.

Given the promising perspective of implicit methods to continuously measure emotions during a given action, including while smelling, eating, and looking at food, and taking into account their lower tendency towards biases and subjective judgments, this section of the review includes studies relying on this latter approach, dividing the literature evidence into sub-paragraphs depending on the biomedical signals investigated.

5.1. EEG Signal, Chemical Senses, and Related Emotions

Electroencephalography (EEG) is a neurophysiological technique that uses electrodes applied on the scalp to measure electrical field activity in the brain region underneath. In particular, wearable EEG are devices that cause little to no discomfort for those examined and do not disturb consumers during evaluations, thus allowing the collection of a good deal of data without limits due to the observation context and longer period of exposure to the stimulus.

The EEG is increasingly applied in food research as a tool for understanding psychological and emotional states through the observation of brain waves [117]. Indeed, when the brain is subjected to a stimulus, i.e., olfactory or gustatory stimuli, it produces electric currents that have different patterns of frequencies associated with different states of arousal. The prefrontal cortex is of particular interest for emotional processing [118] due to its function as a convergence zone of other interconnected structures (anterior cingulate, amygdala, hippocampus, and insula). Two emotional systems participate in emotional processing: the approach system, which facilitates appetitive behavior and is described as a generator of positive affect, and the withdrawal system, which facilitates moving away from aversive stimuli. According to the brain lateralization hypothesis, the left hemisphere is specialized in the approach function, while the right hemisphere intervenes mostly in the withdrawal response [119].

Most of the studies using EEG have analyzed the effect of smelling/tasting drinks on brain activity.

Mignani et al. [120] used EEG to record brain activity in reaction to four different wines (Verdicchio di Matelica DOC, Verdicchio dei Castelli di Jesi DOC, Pecorino Offida DOC, and Soave DOC). The test consisted of three different phases: (i) blind phase, i.e., testing the wine without knowing any information about it; (ii) expectation, i.e., receiving information about the wine (reading labels) without testing it; and (iii) labeled, i.e., reading labels while testing the wine. The two Verdicchio wines were the ones that elicited the highest emotional response in particular during the labeled phase, suggesting the important role of label design in the emotional process. Another study [121] evaluated the effect on brain activity, specifically frontal beta activity, while testing four red wines: two expensive Italian and two expensive Chilean wines, and two cheap Italian and two cheap Chilean wines. EEG recording was performed while watching, smelling, and tasting the wines. Beta activity well discriminated the brain response for the different wines; however, it was not possible to correlate changes in beta activity with wine preferences, as scored by the consumers.

The effect of beer tasting on brain activity was also assessed. In a very recent study, Hinojosa-Aguayo and collaborators [122] evaluated brain response to the visual inspection, smelling, and tasting of four types of beer (two Lager and two extra dry). After each session, the participant had to give a hedonic judgment regarding the beer. Subjects with different levels of experience in tasting beers were enrolled. Beer experts activated more brain components related to recognition memory and fewer brain components related to working memory and attention compared to general consumers. In addition, in expert consumers, the correlation between brain activation and hedonic judgment was higher, suggesting that the experience strongly influences the emotional perception of the products. Implicit response to beers was also tested in a multimodal approach by Viejo et al. [48]. EEG, together with heart rate, temperature, and facial expressions, were recorded while subjects tested nine different types of beer. Results showed that the EEG was able to differentiate between the different beers with spontaneous fermentation beers generating the highest level of attention and liking. In addition, there was a significant correlation between brain measures and the attributes used in the sensory evaluation, in particular, with the level of bitterness.

The study by Lagast and colleagues [123] attempted to evaluate how the degree of acceptance of a particular drink influences brain activity and, thus, emotional response. In a multimodal assessment, the Authors analyzed ECG, GSR, and brain signals in response to the testing of accepted and unaccepted drinks. A universally accepted drink (sweet sucrose solution) and a universally non-accepted (bitter caffeine solution) solution were used together with one personally accepted and one personally non-accepted drink, individually assessed by a questionnaire. Although there was a trend toward a higher emotional response for accepted drinks compared to non-accepted ones, a huge variability emerged among subjects, and thus the results were not significant.

Fewer studies have analyzed brain activity in response to food tasting. In the study by di Flumeri and colleagues [124], EEG was recorded while subjects tasted five savory creams (cheese, bacon, salmon, caviar, and peppers) and two sweet ones (orange chocolate and vanilla chocolate), and frontal alpha asymmetry was calculated. The subjects were also asked to evaluate the taste, in terms of perceived pleasantness (1–10 scale). Sweet flavors produced a pleasantness significantly higher than the savory ones (higher left hemisphere activity). In addition, there is a significant agreement between explicit and implicit measures of pleasantness. Phothisuwan et al. [125] investigated the effect of covering salacca fruit with orange oil on brain activity. Brain activity was recorded while smelling and eating treated and untreated salacca fruits. Treated salacca fruit elicited more brain alpha and beta activity compared to the untreated one both while smelling and eating it, indicating an increased alertness state of the brain. Interestingly, this effect was observed in women, but not in men, probably due to the better sense of smell of the female population. In the study by Brouwer and collaborators [126], the tasting phase was also associated with a cooking experience. Participants were asked to cook and taste two stir-fry dishes, one containing chicken as the main ingredient and the other mealworms. These two products were chosen as they are supposed to elicit opposite emotions in Western cultures. Brain activity was recorded together with ECG and GSR during the different phases of the test. Regarding brain activity, it was observed that during all the phases (exposure, frying, cooling, and eating), there was a higher leftward asymmetry for the chicken dish compared to the mealworm dish, consistently with the approach/avoidance model.

Finally, Maeda and colleagues [127] investigated the odor–taste relationship; in particular, how odor stimulation affects taste perception. Brain activity was recorded in two different conditions: (1) matched condition, i.e., subjects tasted milk chocolate and smelled chocolate paste; and (2) unmatched condition, i.e., subjects tasted milk chocolate and smelled garlic paste. The results of the study showed an increase in theta band activity in the unmatched conditions; theta activity was also negatively correlated with the sweetness score provided by the subject. Since the theta band is correlated to memory-based decision making, it is possible that the perturbation caused by the odor–taste unmatching increased the concentration level of the subjects.

5.2. ECG Signal and Chemosensory-Related Emotions

Among the most popular implicit methods to assess the emotional reactions to odorous stimuli, the ECG signal is normally selected for its reliability and broad information load. Indeed, from the study of the Heart Rate (HR) and its variability (Heart Rate Variability, HRV), several aspects can be derived, including the activity of the Autonomic Nervous System (ANS) that, with its Sympathetic (SNS) and Parasympathetic (PNS) branches, basically supervises emotional reactions of avoidance and relaxation, respectively.

Among the studies investigating HR as the surrogate of the ECG signal, the assessment of emotions generated by different beer samples was studied by two groups [48,128]. The results obtained in both cases led to no differences in the emotional reactions to the various kinds of stimuli; although, subtle changes were detected by the explicit measurements conducted.

On the other hand, an experiment conducted in Mexico [129] aimed to predict consumers' acceptance towards food and odors through facial expressions and biomedical signals. In the study, sweet gums embedding the flavor of mint, pineapple, strawberry, clam, and Gouda cheese were created, whereas partially overlapping odors, referring to pineapple, mint, vinegar, Gouda cheese, and smoke, were administered. According to the authors, facial emotion recognition was not enough to predict the attitude of consumers towards such compounds, whereas the use of Skin Conductance and, to a lesser extent, pulse signals, improves such prediction, highlighting a key role for biomedical signals in this specific domain.

Several levels of sugar concentrations within a chocolate pudding were tested in an Italian research study related to physiological measurements concerned with emotions. In the study, researchers found positive effects on HR variation for increased liking, for perceived bitterness, and for perceived astringent, with variations in sucrose concentrations [130].

As hypothesized, the study about the emotional effects of chemosensory stimulations related to edible substances can fruitfully lead to a deeper knowledge about the intrinsic effects that healthy or unhealthy habits towards food can have on individuals. A study by Finch and colleagues [131] shed light on this topic, highlighting the absence of an effect due to food healthiness on stress and on physiological parameters, including HRV and pre-ejection period, in a broad cohort of women individuals. This fact can have deep consequences in the selection of specific dietary components in presence of unhealthy habits towards food, at least in some individuals.

The act of cooking also represents a very important scenario where chemosensory stimuli are conveyed to an individual. According to the authors, thanks to biomedical signals, it was possible to distinguish between the cooked chicken and mealworms, dishes normally eliciting very different perceptions, and, in this task, the ECG signal plays an important part, given that the extracted variables somewhat interact with the order of cooking of the proposed dishes [126].

When taking into account the attitude towards novel, unexpected food, HR changes demonstrated that it is sensitive to valence, particularly increasing its value under sweet, positively-judged samples (conversely to what was noticed by Lagast and colleagues [123]), whereas significant decreases were noticed when tastes disconfirmed expectations, in a different way with respect to other signals, including Skin Conductance [132]. Under longer periods, ECG signals displayed higher parasympathetically mediated results after training on odorous compounds related to food diluted into white wine, highlighting the significant contribution intrinsic measurements can bring to research concerned with chemosensory training [113].

5.3. GSR and Chemical Sensory Stimuli Emotional Reactions

The Galvanic Skin Response (GSR) obtained from the skin conductance signal is nowadays extensively used in the psychophysiological characterization of an individual. It is then widely also used to check for eventual responses to sensory stimulation in a variety of paradigms. It is often applied in conjunction with other methods and signals, but also as a standalone method for this specific characterization. In the work by Álvarez-Pato and colleagues previously mentioned [129], skin conductance seems to be more sensitive than cardiovascular features to predict the attitude towards the edible compounds tested, conversely to what happened in the study by Martinez-Levy and co-authors [130], where the tonic-only component of the GSR was not enough to characterize the attitude towards food likelihood of the panelists.

As mentioned above, GSR is also used as the elective, standalone method to assess autonomic activity. GSR was seen to decrease with increasing pleasantness, regardless of intensity, in a protocol conducted over a set of four fragrances, two of which elicited positive effect and two negatively judged [133].

In addition, during cooking, GSR was higher when asking participants to deal with unpleasant food with respect to pleasant stimuli; even if in this scenario, the ECG signal was seen to be more sensitive to such stimulation [126], as occurred in a pilot study [134]. These same dynamics were seen in an investigation by Verastegui-Tena and collaborators, where the cardiac signal was seen to be modified by several occurrences, whereas skin conductance changed with respect to novelty and valence, but failed to change with regard to the disconfirmation of expectations. Concerning the types of stimuli, it increased for the bitter sample and decreased for the sweet tastes [132].

A perspective upon acceptability with respect to expected or unexpected stimuli was drafted by Lagast and colleagues, finding a lower latency of the electrodermal response during the tasting of the non-accepted solution [123]. Finally, the administration of familiar stimuli, after training, was seen to decrease the skin response slightly, but significantly, in a cohort of young students [113].

5.4. Other Methods

In some studies, other techniques have been applied to investigate emotional responses associated with food/drink tasting, mostly in combination with the methods described in the previous sections.

In the study by Viejo and co-authors [48], EEG acquisition was coupled with video recording for assessing facial expression and infrared thermal imaging to measure facial temperature. Although facial expression and temperature could not discriminate between beers, there was a significant correlation between disgusted face and body temperature. Notably, the integration of the different modalities was able to classify the emotional response to the beers with about 80% accuracy using a machine learning approach.

Facial expression was also assessed [129] together with GSR and cardiac pulse in response to tasting and smelling different products. Sweet gums with five different flavors (pleasant: mint, pineapple, and strawberry; unpleasant: clam and Gouda cheese) were used as tasters while five odors were prepared for the smelling test (pineapple, mint, vinegar, Gouda cheese, and smoke). All the acquired data were used in a convolutional neural network model to classify the different products. Facial expression alone was not able to classify accurately, while the integration with physiological signals increased the performance.

In the study by Beyts et al. [128], temperature, respiration, and facial electromyography (EMG) recordings were added to the HR registration. These signals were acquired while exposing subjects to different beer aromas. In particular, facial EMG recording was obtained by measuring corrugator supercilii and zygomatic major muscle activity. While temperature and respiration did not discriminate among the different samples, facial expressions showed a significant response to aroma valence. In particular, more corrugator activity, indicative of frowning, was observed in response to the unpleasant aromas.

Finally, a relatively novel neurophysiological technique, the functional near-infrared spectroscopy (fNIRS), was applied in one study by Park and colleagues [135]. In particular, the Authors analyzed cerebral response while chewing two types of apples and a dummy. Food preference was determined by measuring the determination rate, i.e., the difference in brain activity while chewing the preferred and nonpreferred food. First, the brain oxygenation signal significantly changed while chewing apples compared to a dummy. Second, it was observed that brain activation could differentiate between the preferred and unpreferred apple with a high discrimination rate, suggesting that the fNIRS technique could be effective in the psychophysiological monitoring of food stimuli.

6. Discussion

As discussed in Table 4, each different technique suitable for food quality assessment (i.e., panel test; consumer test; e-sensors such as e-nose, e-tongue, and e-eye) shows some potential and limits that need to be considered for the choice of the best analytical approach as a function of the context together with the technological issues to be achieved from time to time.

Among the techniques useful for food quality assessment, the panel test [136] occupies a prominent place, thanks also to the recent development of effective methods for the statistical analysis of data. In particular, the main advantage shown by the use of sensory analysis is to have a complete and reliable description of the main sensory features of a product, even with the aim to measure its overall quality.

On the contrary, given that sensory analysis is time-consuming and expensive, when the aim is to determine the presence of some specific compounds, or to follow the change in some well-identified food's features during production and/or storage, the use of e-senses can be a valuable alternative.

Table 4. Application, potential, and limits of the methods discussed in Sections 3 and 4.

Method	Main Field of Applicability	Potential	Limits	Bias Sources	Tools for Bias Reduction
Panel test	Food quality assessment Sensory shelf life New products/new processes development	Overall characterization of food's features given by the integration of the stimuli from all the five senses	Time-consuming and expensive	Individual differences Physiological bias Psychological bias	Panel selection and training Taster profiling Official method for assessing Statistical analysis of results
Consumer test	Food quality assessment Acceptability test	Overall characterization of food's features aimed at evaluation of consumer's acceptability and marketing studies.	Time-consuming and expensive Very high number of consumers to be recruited	Context Consumer profile Past experiences Socio-cultural background	Taster profiling Statistical analysis of results
E-senses (i.e., e-nose, e-tongue, and e-eye)	New products/new processes development Food quality/safety Assessment during storage Food origin/certification/adulteration	Precise and immediate quantification of specific substances inside a product	No match with the final perception given by the human senses Calibration and algorithm development time consuming	Matrix effect Operating conditions adopted Sampling method	Statistical analysis Chemometric approach Calibration and algorithm improvement

In addition, when human perceptions represent the main tool for food characterization (both in panel tests and in consumer studies), considering that emotions elicited by foods influence the output of the sensory analysis, emotions themselves should be always taken into account and measured when possible or necessary. The measurement of emotions is not straightforward and many different methods are available (see Table 5 for the most popular ones among implicit ones). As such, a deep analysis of the potential and limits of the different methods, also in relation to the specific context and goals, is surely necessary. In general terms, it is notable that implicit methods are less subjected to biases related to a person's judgment towards a given stimulus with respect to explicit methods, which, in turn, completely rely on such principles. However, as seen in Table 5, implicit methods have also significant drawbacks that should be taken into account when selecting the most useful approach to be eventually adopted.

Table 5. Application, potential, and limits of the bioengineering methods. EEG: electroencephalogram; ECG: electrocardiogram: ANS: autonomic nervous system.

Method	Main Field of Applicability	Potential	Limits	Bias Sources
EEG	Study of the emotional reactions elicited at cortical level	Direct evaluation of the emotional, cognitive processes	Complexity of the instrumentation, artifacts characterizing the signal, cost	Electrodes placement, discomfort for the subject tested
ECG	Study of the ANS activation in response to emotional stimuli	Assessment of the indirect effects of sensory stimulation in an easy, understandable, cost-affordable manner	Indirect method, not suitable to directly study cortical effects of stimuli	Model between central and peripheral response not always available
Skin Conductance	Study of the ANS activation in response to emotional stimuli, mainly related to sympathetic activation	Assessment of the indirect effects of sensory stimulation in an easy, cost-affordable manner	Indirect method, not suitable to directly study cortical effects of stimuli	Model between central and peripheral response not always available

7. Conclusions

The mechanisms beyond the whole cognitive process that obtains a food sensory characterization by trained judges during a panel test and/or that drives a consumer's food choice or rejection involves individual differences at both physiological and psychological levels. In particular, the latter is mainly based on context, socio-cultural background, past experiences, memory, emotions, etc.

Starting from a critical review of the recent literature on the topic, the main conclusion that we can provide is that a multidisciplinary approach including Food Technology, Sensory analysis, and Bioengineering can represent the principal topic for future trends in the field to obtain the final goal of improving food quality and/or meeting consumers' expectations. In this context, the merging between intrinsic and extrinsic approaches could represent an innovative way to optimally manage the trade-off between accuracy of the information and feasibility of investigation, also allowing for a sort of validation of physiological reactions versus subjective perception and attitude towards a particular sensation.

To the best of our knowledge, recent literature related to research projects aimed at investigating the feasibility of a synergy strategy, and then comparing it with the use of single approaches, is still lacking. Future studies should take into account this aspect and make the best use of both approaches to solve the problems characterizing the majority of the studies published up to now.

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