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Emerging Methods for the Evaluation of Sensory Quality of Food: Technology at Service

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Abstract

Purpose of Review Sensory evaluation holds vital significance in the food sector. Typically, humans conduct sensory analysis. Humans, being the ultimate consumers, assess food traits effectively. However, human judgment is influenced by various factors. Hence, countering subjectivity is crucial for objective evaluation while retaining hedonic insights.

Recent Findings Food's sensory assessment primarily employs humans. Various techniques differentiate, depict, or rank food. Modern sensory tools, aiming to enhance objectivity and reliability, are emerging to supplement or supplant human assessment. This advance can bolster quality, consistency, and safety by mimicking human senses such as smell, taste, and vision, mitigating risks tied to human assessors.

Summary This paper provides a review about sensory analysis of food using technological methodologies. A review of different technological tools to analyze sensory characteristics of food, as well as a discussion of how those technological tools can relate to humans' perception of food is presented.

Keywords Sensory evaluation · Spectroscopy · Biometric measurements · Artificial senses

Introduction

Sensory analysis is a scientific method used to evaluate and understand the human perception of food, drink, and other consumer products. The sensory evaluation of foods presupposes the analysis of their intrinsic and extrinsic characteristics. While the intrinsic characteristics are related to how the physicochemical characteristics of food are perceived by the sense organs, such as its appearance, aroma, texture, and flavor, using the senses of sight, smell, taste, touch, and sometimes sound, the extrinsic characteristics have a more subjective character, relating to the way consumers react to the former. We speak of sensory science in the first case and consumer science in the second. Traditional sensory evaluation methods (discriminative, descriptive, and hedonic [1]) rely on human senses to assess the quality and characteristics of a product. While these traditional methods have been effective, they can be time-consuming, expensive, and subjective due to their reliance on human evaluators. Moreover, they may not fully capture the complete range of sensory experiences associated with complex products like multi-component foods or beverages.

Recognizing the considerable time and economic investments required for training assessment panels in descriptive analysis, numerous innovative methodologies for sensory characterization emerged in the early 2000s [2]. These methodologies prove to be less time-intensive and more adaptable and can involve partially trained assessors and even consumers. They generate sensory maps that closely resemble the outcomes of traditional descriptive analysis conducted with highly skilled panels. These novel techniques, mentioned and used by various authors, employ diverse approaches, such as methods centered on the assessment of specific attributes (such as intensity scales [3], check-all-that-apply questions or CATA [4–8], flash profiling [9], and paired comparisons [10, 11]), methods focused on evaluating overall differences (sorting [12], projective mapping or Napping® [5, 13–15]), methods involving the comparison with product references (polarized sensory positioning [5, 16]),

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and methods based on an open, comprehensive evaluation of individual products (Open-ended questions [17]). Additionally, hedonic methods such as just about right (JAR), ideal profile method (IPM), relative preference mapping (RPM), and temporal dominance of sensations (TDS), among others, were reported [18]. Nonetheless, the above methodologies still exhibit certain limitations.

In response to the need for more objective and comprehensive assessments of sensory attributes of food, and perceive how consumers react to them, emerging methods have gained attention. Novel techniques such as the use of biometric measurements (including facial expressions, heart rate, skin conductance, body temperature, and eye-tracking) [19, 20•, 21, 22], virtual environments (virtual and augmented reality) [23, 24], and artificial senses (e-nose and e-tongue [25•, 26]) are being explored as tools to understand the complex nature of human responses in sensory tests [27, 28••, 29]. Other methods include chromatography [30] and spectroscopy [29, 31], which employ sensors to detect and quantify specific compounds associated with flavor, aroma, and texture. Digital imaging (E-eye) is another emerging method that uses cameras and algorithms to analyze the visual characteristics of products [25•, 32]. Additionally, consumer-based methods such as social media analysis and online surveys have become valuable tools [33]. These emerging methods offer advantages such as increased objectivity, faster data collection, and the ability to capture a broader range of sensory experiences. However, they also have limitations, such as high costs and the need for specialized equipment or expertise.

Both traditional and emerging sensory evaluation methods have their strengths and weaknesses. The choice of method depends on the specific needs and goals of the food industry. By combining different methods, the industry can obtain a more comprehensive understanding of the sensory attributes of their products and make informed decisions regarding product development, marketing, and quality control. Precise sensory evaluation methods are crucial in the food industry for ensuring consistency, safety, efficiency, and compliance with regulatory standards. Failure to implement appropriate sensory analysis can lead to negative consequences such as customer dissatisfaction, compromised public health, production inefficiencies, and legal repercussions(Fig. 1).

The purpose of this paper is to provide a comprehensive review of emerging methods in sensory analysis that can enhance our understanding of sensory attributes in the food industry. The review focuses on various techniques, including spectroscopy, artificial senses, and biometric measurements. These methods offer innovative approaches to obtain more objective and comprehensive assessments of sensory attributes. Despite some limitations, ongoing advancements and research continue to address these challenges, making emerging methods valuable tools in enhancing product development, consumer understanding, and quality control.

Spectroscopy

In this section, the significance of diverse spectroscopy methodologies in food analysis is elucidated, affirming their pivotal role in upholding stringent quality and safety control measures, ultimately contributing to consumer satisfaction and safety. The emergence of spectroscopic techniques presents objective, swift, and non-destructive tools for assessing food quality [34]. Within the most common spectroscopic techniques used in food science, visible and near-infrared spectroscopy, Fourier-transform infrared spectroscopy, and Raman spectroscopy in combination with chemometric methods have been used in assessing the characteristics of several products such as dairy and honey products [35–37], meat and seafood [38–41], cereals [42–45], vegetable oils [46–48], and coffee [49, 50]. In recent years, hyperspectral imaging has emerged as a valuable tool in food science, enabling the determination of composition parameters such as moisture and protein content. A rapid, nondestructive, and noncontact analytical method is useful to assess the quality and safety of meat and meat products, vegetables and fruits, cereals, aquatic products, and others [51].

Moreover, it has been successfully utilized to study the optical properties of various food products including oils, juices, milk, yogurts, and eggs [52]. Similarly, nuclear magnetic resonance (NMR) has found significant applications in food science, food analysis, and food quality control [53]. NMR has proven particularly effective in the analysis of milk and milk products [54–56], enabling characterization based on geographic origin and feeding diet [57]. It has also been employed in studying the effects of freezing on pasta filata and non-pasta filata cheeses [58], as well as in the analysis of meat [59, 60], edible oils [61], cereals and beer [62, 63], and fruits and vegetables [64]. These advanced techniques (hyperspectral imaging and NMR) have demonstrated their efficacy in providing valuable insights into the composition, physical characteristics, and quality of various food products. Their successful applications in diverse areas of food science contribute to improved food analysis, quality control, and understanding of food properties.

The assessment of most physicochemical parameters in food is typically linked to sensory properties. When it comes to determining the ultimate quality of a product based on consumer preference, sensory analysis by trained sensory panels serves as the key. However, it is important to note that maintaining sensory-trained panels can be challenging, costly, and time-consuming. Considering these challenges, the utilization of spectroscopic techniques as non-destructive, fast, and precise methods has been explored as

Fig. 1 The integration of technology enhances objectivity and efficiency in food sensory evaluation

an alternative to traditional sensory panels. While there have been numerous studies published in this area, only a few directly relate spectroscopic and chemometric techniques to sensory traits. Table 1 shows a selection of studies that related the spectroscopy techniques and chemometrics techniques with sensory attributes in various food products.

Indirectly related but largely influencing the food sensory quality is the fat content, particularly the intramuscular fat or marbling, which is one of the most important characteristics of meat quality. It is often associated with the meat's color, another determining factor for consumers when purchasing meat. Hyperspectral imaging has been successfully applied to characterize intramuscular fat distribution in beef and classify beef marbling with great accuracy [80, 81], and in pork [82]. It has also been applied in lambs [83] with promising results.

For predicting the intramuscular fat, NIR spectroscopy has also been used [84] showing the potential of Vis–NIR to predict moisture and IMF using homogenized pork muscles [85] and for example to predict chemical composition in goats [31], and in beef [86]. In sheep and goats, an extensive revision on the use of non-destructive imaging and spectroscopy techniques for the assessment of meat quality was made [87].

The detection of fat content, an important factor related to fish quality, in salmon or grass carp is also achievable using hyperspectral imaging [88–90]. Additionally, a multispectral model has been developed to detect changes in docosahexaenoic acid (DHA) and eicosapentaenoic acid (EPA) levels in fish fillets [91]. These two n-3 polyunsaturated fatty acids have been proven to offer beneficial health effects, particularly for cardiovascular and inflammatory conditions. Also, in fruits, hyperspectral technology is used to detect characteristics related to sensory quality as in apples for predicting bruise susceptibility [92]. The recent advances and applications of hyperspectral Imaging in detecting, classifying, and visualizing quality and safety attributes of fruits and vegetables were summarized in a revision by Lu et al. [93].

Table 1 Food sensory evaluation studies using different spectroscopy methods

Food product	Spectroscopy technique	Sensory evaluation	Reference
Coffee (expresso)	NIR associated	NIR can be successfully applied for sensory quality estimation	[65]
Coffee (expresso)	Nosespace (NS) with (PTR-Tof–MS)	A better understanding of coffee flavor perception	[66]
Cheddar cheese	NIR	Predict sensory attributes (crumbly, rubbery chewy, mouthcoating, and mass forming)	[67]
Cheese	NIR	Sensory attributes and instrumental texture measurements were modeled with sufficient accuracy	[68]
Milk and ripened cheese	NIR and PTR-Tof–MS	High rate of discrimination according to the farming system using sensory profiles. Interesting as a research tool. Not at an industry level	[69]
Tea	Micro NIR and CVS	Portable and low-cost tool to evaluate the black tea fermentation quality	[70]
Black tea	NIR and CVS	A useful strategy to classify black tea	[71]
Pineapple	FLUO	For odor, the FLUO sensor achieved the highest overall performance	[72]
Peas	NIR	Potential for predicting the sensory quality (texture and flavor)	[73]
Walnut kernels	NOR	Excellent potential for monitoring the quality (rancid, nutty, sweet bitter)	[74]
Pork	NIR, Raman, fluorescence, NMR	Fluorescence spectroscopy and TBARS were able to follow the WOF during storage	[75]
Beef	NIR (NIRR and NIRT)	The better prediction of sensory attributes was obtained in the NIRR mode	[76]
Beef	Raman	Raman spectroscopy technology can predict texture, tenderness, and overall acceptability	[77]
Lamb	NIR	Intramuscular fat and water are accurately predicted by NIR, related to sensory characteristics	[78]
Beef	Raman	High potential to predict the sensory quality traits of young dairy bull beef	[79]

NIR near-infrared spectroscopy, *PTR-Tof–MS* analysis via proton transfer reaction-time of flight-mass spectrometry, *CVS* computer vision system, *FLUO* Fourier-transform infrared fluorescence, *NMR* nuclear magnetic resonance, *WOF* warmed-over flavor, *NIRR* NIR in reflection mode, *NIRT* NIR in transmission mode

With the advancement of computer image processing technology, various procedures such as ultrasounds and computed tomography have been employed to obtain muscle images for assessing intramuscular fat through computer image analysis. The computer vision–based marbling assessment has been performed in beef [94–96], pork [97, 98], and lamb [99] and also in cheese quality evaluation [100] or even in fruit classification [101]. Additionally, computer vision has been employed for the assessment of color grading in beef fat [102] and the color of salmon fillets [103].

Spectroscopy techniques have emerged as powerful tools for assessing food quality attributes in a rapid, nondestructive, and objective manner. While their applications in food science and sensory analysis have already shown great promise, the future holds even greater potential for these techniques to revolutionize the assessment of sensory food quality. Continued advancements in technology, data analysis, and integration with other disciplines will propel these techniques to new heights. By leveraging these tools, the food industry can optimize product development, ensure consistent quality, and meet the ever-evolving demands and preferences of consumers. Spectroscopy techniques are poised to revolutionize sensory food quality assessment and drive innovation in the field of food science.

Artificial Senses

Electronic Noses and Tongues

The electronic tongue (E-tongue) and electronic nose (E-nose) are recent tools that can redefine the traditional methods of evaluating food attributes, bringing a data-driven and objective dimension to the intricate world of taste and aroma analysis. Both align with the imperative for precise and swift quality assessment of food products, driven by the paramount importance of safety considerations within the food supply chain.

The electronic tongue, known as the E-tongue, serves as a versatile instrument for decoding taste profiles and can be constructed using diverse measurement principles, including optical, electrochemical (potentiometric, impedimetric, voltammetric, or amperometric), mass-based, and spectroscopic detection techniques [104]. The potentiometric E-tongue with polymeric lipid sensors stands out as the most extensively employed option. [105]. Resembling an artificial palate, it is a multisensory apparatus designed to mimic the human gustatory system. Comprising an array of chemical sensors that respond to various taste compounds, the electronic tongue generates unique response patterns, or sensor "fingerprints," for each food sample that is analyzed. These fingerprints are subjected to advanced statistical analyses and machine learning algorithms to decode taste attributes such as sweetness, bitterness, saltiness, sourness, and umami. The E-tongue bridges the gap between technology and human evaluation. Its ability to swiftly discern complex taste profiles showcases its potential in various food sectors, such as in the meat area. Some different examples of potentiometric electronic tongue applications in meat, poultry, and fish are pork/chicken adulteration in minced mutton [106]; salt taste intensity effect of saltiness-enhancing peptides in meat products [107]; flavor profiles of sheep breeds [108]; crayfish flesh flavor evaluation due to different dietary protein sources [109]; flavor compounds in dry-cured pork with different salt content [110]; and physical–chemical and microbiological changes in fresh pork meat under cold storage [111].

Parallelly, the E-nose mimics the human olfactory prowess by identifying and distinguishing diverse odors and aromas. This device is also an emerging approach capable of detecting and differentiating between various aromas through an array of electronic sensors (usually, semiconductor gas sensors). The data harnessed from these sensors also undergoes sophisticated algorithms to craft distinct aroma patterns, revealing the nuanced scent signatures of diverse food samples. The E-nose is also a non-destructive and low-cost system that can be applied to evaluate food quality, safety, and adulterations since it is capable of characterizing food quality factors [112].

Numerous instances exemplify its application in the realm of highly perishable muscle-based foods, including meat, poultry, and fish. These instances demonstrate its potential as a promising tool for evaluating quality attributes such as freshness, spoilage detection, and the identification of adulteration in meat products. For instance, the presence of pork in meat and meat sausages [113], the adulteration of beef meat involving varying proportions of pork meat [114, 115], and the blending of minced mutton with duck [116] were subjected to analysis using an E-nose. The outcomes of these analyses revealed acceptable accuracy, markedly shortened detection time, and good detection efficiency. Similar results were obtained in studies centered on beef spoilage [117], pork spoilage [118], and fish meal spoilage [119], as well as the freshness of chicken [120], freshness of pork [121], and shelf-life evaluation of meat and fish products [122, 123].

Aroma Tests

Aroma tests involve evaluating how consumers perceive food aromas by exposing them to various scents and rating their preferences and intensities. These tests utilize specialized sensory evaluation methods like olfactometry or gas chromatography–olfactometry, allowing precise presentation and analysis of aromas. Human evaluation remains essential despite using technology. While sensory approaches provide valuable data on the overall nature and intensity of aroma mixtures, they may not fully capture the intricate interactions during odor perception. To address this, researchers use models based on complex mixture compositions to understand odor nature and intensity [124]. Similarly, headspace solid-phase microextraction coupled with gas chromatography–mass spectrometry was employed [125, 126] to study the aroma components of dark tea varieties. Odor activity value calculation and aroma profile tests were conducted to understand the aroma characteristics of "aged fragrance" and "fungi flower aroma." Moreover, Hawko et al. [124] utilized an experimental mixture design with sensory analysis to develop numerical models converting chemical data into sensory data. They used Langage des Nez® (LdN), an objective odor-nature description method, to characterize the odor nature for each mixture and modeled the variation in odor nature based on mixture composition. It is worth noting that aroma tests can also be associated with electronic noses (E-nose).

Electronic Eye

An electronic eye (E-eye) is a computer vision technology that converts optical images using an image sensor, eliminating subjective human vision [127]. It finds applications in food quality evaluation [128], providing fast, accurate, and non-destructive assessment of product shape, size, color, and texture [129]. This versatile technology integrates mechanics, optics, electromagnetic detection, colorimetry, spectrophotometry (discussed in detail previously), digital video, and image processing, making it valuable for monitoring visual quality changes during production [130, 131]. Appearance and color are vital factors in consumers' quality experience, and the E-eye ensures reliable and consistent monitoring [132]. It offers objectivity, reproducible measurements, and data storage for product traceability and does not affect product consistency or texture. The E-eye allows in-depth analysis and can correlate with sensory panel assessments [133]. Its applications extend to agricultural and food industry processes, monitoring product aging, detecting foreign substances, verifying color changes during food processing, and assisting the brewing industry in automation for optimizing product quality [134–137].

Conventional image analysis is highly valuable for studying meat products' appearance characteristics due to its cost-effectiveness, consistency, speed, and accuracy in automated applications [138–140]. Extensive research has been conducted on the use of the E-eye for quality evaluation in various fresh meat and meat product applications. Its versatility includes assessing color [141, 142] and monitoring color changes [143, 144], grading marbling level [145–147], quality prediction [148] and control [32], defect detection [149–151], and sorting operations [152–154]. Color is a critical attribute in meat and meat products, closely linked to freshness, and color discrepancies may lead to the rejection of meat cuts [155]. Studies have shown favorable correlations between E-eye and colorimeters, with good results for lightness and reasonable regression coefficients for redness and yellowness in chicken meat [156]. Globally, E-eye technology holds the potential to bring advantages to the recent trends in automation and online control in food production [157].

Biometric Measurements

The use of neuro-physiological data in models of consumer choice is gaining popularity. Eye tracking, facial expressions, and electroencephalography (EEG) are some examples [19, 29]. Food experiences are shaped not only by the inherent qualities of the food such as its appearance, taste, texture, and flavor but also by external factors like visual branding and the consumers' past encounters with the food. Advancements in automated facial expression analysis and heart rate detection, utilizing remote photoplethysmography (RPPG) [20•] based on changes in skin color, have made it possible to monitor food experiences through video images of the face. This type of methodology/technology can be applied remotely using video images, opening opportunities for large-scale testing in consumer science, and allowing researchers to conduct studies with a broader reach [20•, 158].

Facial Expressions

Numerous researchers globally have extensively documented the recent sensory method of measuring facial expressions [20•, 21, 22, 159]. When exposed to stimuli, humans unconsciously display emotions, often through involuntary facial movements, which researchers use to understand emotional states. While psychologists have employed this approach for a considerable time, its popularity among sensory scientists has grown due to the integration of automated mechanisms for quick response processing [160]. Software solutions like FaceReader™, developed by Noldus Information Technology in Wageningen, The Netherlands, or Affectiva Affdex®, created by Affectiva Inc. in Waltham, MA, USA, utilize built-in algorithms to detect and measure various facial movements. These algorithms then translate the captured signals into emotional responses [161]. Facial expressions have proven to be valuable in assessing consumers' emotional reactions to a variety of products, including chocolate [158, 162], beers [163, 164], sports drinks [22], meat products [165], yogurt [166], and soy sauce [20•]. Table 2 provides a summary of the results obtained in studies where facial expressions were utilized to evaluate food products, showing great potential for the use of this technology.

Furthermore, the findings from a study exploring whether facial expressions during food consumption could provide additional insights into temporally dynamic, implicit responses to foods beyond self-reported conscious measures [167] suggest that facial electromyography (EMG) has the potential to aid in understanding consumer responses to food in future research. However, while it showed a connection to the hedonic liking of commercially available chocolate samples, the sensory variations in these samples made it challenging to use facial EMG to distinguish samples based on mean liking, which is better achieved through self-reporting methods.

Exploration of how sensorial perceptions change with age and whether biometric analysis can help uncover unconscious consumer responses was made [168], focusing the investigation on the effects of consumer age on facial expression responses (FER) while consuming beef patties with varying firmness and taste. Two age groups were considered—younger (22 to 52) and older (60 to 76). Video images were recorded during the consumption, and the FERs were analyzed using the FaceReader™ software. Younger participants exhibited higher intensity for happy, sad, and scared expressions but lower intensity for neutral and disgusted expressions compared to older participants. Additionally, interactions between age and texture/sauce showed minimal FER variation in older individuals, while younger participants showed significant FER variation. Notably, younger participants displayed the lowest intensity of happy FER and the highest intensity of angry FER when consuming the hard patty. The addition of sauce led to a higher intensity of happy and contempt expressions in younger consumers but not in older consumers. Results demonstrated a successful differentiation between the unconscious responses of younger and older consumers by analysis of FER using FaceReader™. By utilizing automatic facial coding (face reader) and skin conductance response (SCR) measurements along with context information during the observation, olfaction, manipulation, and consumption of liquid foods by children [169], the study observed that the methodology employed successfully distinguished the three samples throughout these stages. The most effective discrimination between samples occurred during the manipulation task.

Table 2 Results from studies applying facial expressions when consuming food/beverages

Product	Result	Reference
Commercial breakfast drinks	ANS responses (including heart rate, temperature, and skin conductance) and facial expressions were different depending on the type of food sample evaluated	[159]
Chocolate	Video advertisements evoked a higher emotional response compared to perfumes, and perfumes elicited more emotions than chocolates. Discrimination between video advertisements and perfumes was achieved through a facial expression measurement protocol, revealing a temporal emotional response for these products. However, no discrimination was found between different chocolates, and they did not elicit a temporal emotional response	[158]
Sports drinks	The participants' implicit emotional responses, as reflected in their facial expressions, indicated a higher level of engagement with energy drink B when compared to energy drink A. The study revealed that the overall liking and the explicit (CATA) and implicit (facial expressions) emotional measurements demonstrated weak to moderate correlations	[22]
Soy sauce	The main factors influencing liking and arousal were the specific tastes, while branding and familiarity had minimal impact on these aspects. On the other hand, facial expressions were primarily influenced by branding and familiarity, with specific tastes playing a secondary role	[20•]
Beer	The facial expressions "Lip suck" and "Lip press" have the potential to serve as effective indicators for predicting beer choices after tasting. While the current study did not confirm reproducibility, it was observed that "Lip suck" before swallowing was associated with a reduced number of beer choices. On the other hand, "Lip press" after swallowing demonstrated a positive correlation with beer choices and was established as a consistently replicable finding	[163]
Yogurt	Using the facial expression recognition (FER) approach, the study successfully differentiated the acceptability of various yogurt samples, particularly identifying the disliked ones. However, it should be noted that this method only explained a small portion of the variability in the consumer data. Moreover, the FER results also revealed cultural differences, with each culture displaying a distinct set of emotions in response to the tasted yogurts	[166]

Other Autonomic Nervous System Responses

Apart from analyzing facial expressions, several other biometric techniques can be employed to evaluate the emotional responses of participants or panels toward different stimuli. These techniques, implicit measurements of food experience [170], include measuring heart rate [20•], body temperature [159], and skin conductance [171]. Furthermore, a recent review focused on the application of specific neuroscientific methods in consumer sensory analysis, particularly highlighting the use of EEG and eye movements [172]. Techniques mainly used for collecting brain signals (EEG, electroencephalography; fMRI, functional magnetic resonance; and MEG, magnetoencephalography), active muscle fibers electric signals (EMG, electromyography), and heart-beat rates (ECG, electrocardiogram) [173] are referred as new non-invasive sensory approaches in food sensory analysis and market survey. The application of this novel technology has shown to be appealing in the context of sensory and consumer sciences, complementing information from explicit measures of the sensory properties themselves obtained by objective evaluation of a taste panel. As referred by Viejo et al. [164], the combination of sensory and biometric responses in consumer acceptance tests proved to be a dependable tool for beer tasting, enabling the extraction of valuable information from consumers' physiology, behavior, and cognitive responses.

Electrophysiology, specifically using EEG, measures brain electrical activity in response to sensory stimuli, providing insights into neural patterns linked to different sensory experiences, such as sweetness or bitterness. This information helps in understanding how consumers perceive food and how sensory perception affects preferences and behavior. EEG enables predictive models for sensory perception, optimizing food formulation and packaging to cater to diverse consumer groups. Several studies have utilized electrophysiology for this purpose [174–178].

When applying biometric techniques to food-related studies, the results can differ based on the type of product being evaluated and the cultural background of the participants or panel involved. Table 3 resumes the results from studies made with the application of biometric measures when consuming food.

Virtual Reality and Immersive Techniques

The environment in which consumers taste their foods or beverages can significantly affect their sensory responses [24]. Traditional sensory tests use isolated booths to eliminate external interference, but some argue that this lacks real-life context [181]. To address this, researchers conduct consumer tests in real-world settings like restaurants and kitchens [182], though this can be time-consuming and costly. Immersive virtual reality offers a promising solution,

Table 3 Biometric studies on sensory evaluation of food

Product	Technology	Results	Reference
Soy sauce	Heart rate	Both RPPG (remote photoplethysmography) and PPG (photoplethysmography heart rate) heart rates demonstrated effects associated with branding and familiarity. Nevertheless, it became evident that the RPPG heart rate measurement necessitates additional refinement, given its tendency to underestimate heart rate when compared to PPG. Additionally, RPPG heart rate exhibited reduced sensitivity to variations over time and during different activities, like viewing brand information and tasting	[20•]
Sucrose (sweet) and quinine (bitter) solutions	Heart rate and skin conductance	Heart rate decreased when tasted samples contradicted expectations and increased when the samples confirmed expectations. The sweet sample elicited larger heart rate increases compared to the bitter sample. The second experience led to heart deceleration Skin conductance was influenced by novelty and valence, not by disconfirmation of expectations. Increased with the bitter sample and decreased with the sweet sample. Skin conductance was consistently higher during the first experience compared to the second Findings suggest cardiac responses are more sensitive to novelty and disconfirmation of expectations, while skin conductance responses primarily reflect novelty and valence	[171]
Wine	ECG and skin conductance	After a brief and intensive sensory training focused on wine tasting, the participants' autonomic nervous system (ANS) activity shifted toward a less sympathetic response once they became familiar with the odorous compounds	[179]
Beer	Heart rate, temperature from the eye region, and EEG	A negative correlation was observed between body temperature and liking of foam height and stability, indicating consumers tend to prefer beers with greater foam when their body temperature is lower. Theta signals showed a positive correlation with bitterness, suggesting consumers tend to prefer beers with lower bitterness when their theta signals are higher. Overall, consumers' beer preferences are influenced by both conscious and unconscious sensory responses, with a preference for beers with greater foam and lower bitterness	[164]
Beers	EEG	Participants evaluated beer sensory properties as relatively similar. However, during the gustatory phase, experts and general tasters displayed differences in brain activation related to memory processes, while general tasters and consumers showed differences in brain activation linked to hedonic processing There was an apparent stronger relationship between self-reported quality judgments and EEG activity, particularly in recognition and working memory components, in experts than in other groups. General tasters and consumers also exhibited connections, primarily involving hedonic processing and recognition memory components. Relationships differed significantly, especially between experts and consumers, with variations in the involvement of working memory components Results suggest that beer experts have a more efficient pattern of gustatory processing and demonstrate a better alignment between explicit (judgments) and implicit (EEG) measures of the sensory and hedonic quality of beers	[180]

allowing the simulation of various contexts in controlled laboratory facilities. This approach has been valuable in studying the sensory impact of different environments, such as tasting wines and chocolates [183, 184]. Augmented reality is another option, integrating virtual elements into the real world to assess consumer perceptions and emotional responses, as demonstrated in tasting yogurt products [185].

In a preliminary study [186], the impact of immersive consumption contexts on food-evoked emotions was investigated using facial expressions and subjective ratings. The findings revealed the following three key points: (1) recreating physical and social consumption contexts in the laboratory influenced general and food-evoked emotions, as evident from both self-reported emotions and facial expressions; (2) both the type of food and the context independently influenced food-evoked self-reported emotions and facial expressions; (3) while there were similarities between self-reported, food-evoked emotions and facial expressions, some differences were also observed, highlighting the additional value of measuring facial expressions in understanding emotional responses to food.

Conclusion

Never underestimating sensory evaluation performed by humans, in a world propelled by innovation, these technologies beckon a paradigm shift in sensory analysis, fusing cutting-edge prowess with culinary finesse. As they continue to evolve, the new techniques promise a new frontier where objectivity and data-driven insights heighten our appreciation of food attributes.

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Declarations

Ethics Approval and Consent to Participate This article does not contain any studies with human or animal subjects performed by the authors.

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Competing Interests The authors declare no competing interests.

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Papers of particular interest, published recently, have been highlighted as:
- • Of importance
- •• Of major importance

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