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Review

Recent Applications of Potentiometric Electronic Tongue and Electronic Nose in Sensory Evaluation

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ABSTRACT: Electronic tongue (e-tongue) and electronic nose (e-nose) have been widely used to determine food products' taste, aroma, and flavor profiles. Several researchers and industries have recently attempted to find relationships between these e-senses and human sensory panels to ultimately replace sensory panels or use them as a viable alternative to time-consuming and expensive traditional sensory evaluation (e.g., consumer acceptance testing or descriptive sensory analysis). This study investigated the recent applications of e-tongue and e-nose in the food and beverages sectors and their relationships with human sensory panels, including a trained sensory panel and naïve consumers. According to several studies, the e-tongue, e-nose, or a combination of e-tongue and e-nose can be an effective and powerful tool for rapid assessment of sensory profiles and quality detection with significant correlations with human sensory data. These instruments are also often reported to be more sensitive to detect subtle changes/differences that the human panel cannot detect. Future trends and projections of the e-tongue and e-nose with limitations are also discussed.

Keywords: electronic nose, electronic tongue, e-senses, sensory profiles

INTRODUCTION

Recently, novel methods, including electronic tongue and electronic nose (e-senses), have become an essential focus of researchers and many industries because they can serve as alternative methods to human sensory testing. This is because these e-senses can overcome the problems of sensory methods using human sensory panels, including subjectivity, panelists' sensory fatigue, high expenses, and a more time-consuming method (Modesti et al., 2022). Furthermore, these e-senses can be considered fast and valid alternative instruments compared to other analytical techniques, including spectroscopy, which are very sensitive, selective, and expensive, with needed pretreatment steps for sample preparation. These e-senses were developed to evaluate food and beverage quality or to assess human sensory perception more objectively. Researchers and industries have been trying to find relationships between e-senses and human panel data. This study will focus on taste, aroma, and flavor profiles collected using an electronic tongue, electronic nose, or a combination of e-tongue and e-nose, respectively, and how these instrumental sensory profiles complement human sensory perception with the potentials and challenges of these e-senses.

REVIEW METHODOLOGY

This study was undertaken in the PubMed and Google Scholar databases in September 2022 with a limit as to the publication period, 2019～current. Emphasis on the most recent studies was due to the technological advances of e-senses. The following keyword combinations were used to search for relevant articles; "electronic", "tongue", "nose", "correlation", and "sensory". Of the 5,840 articles, we narrowed it down to 283 articles with a keyword, "Alpha MOS", which is one of the leading manufacturers of e-senses. This was to focus on the same type of e-senses (i.e., potentiometric e-tongue), especially e-tongue, in this review. However, we did not limit our search to only "Alpha MOS", but included other potentiometric e-tongues in this review.

DATA COLLECTION

The authors evaluated the 283 articles; the first analysis

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was conducted based on the titles and abstracts after excluding the review articles. A careful reading of all studies resulted in only 36 original research articles with either a correlation analysis between the e-senses and human sensory perception or a comparison of the two methods.

OVERVIEW OF E-SENSES (ELECTRONIC TONGUE AND NOSE)

Electronic tongue (e-tongue) or electronic nose (e-nose) mimics the human tongue or human nose to analyze taste-related and volatile compounds based on an array of sensors with a suitable integrated pattern recognition system (Cabral et al., 2009; Buratti et al., 2018; Shi et al., 2018; Orlandi et al., 2019).

The used common e-tongue sensors are potentiometry, voltammetry, and impedance spectroscopy (del Valle, 2017). The most widely used commercial potentiometry e-tongues are Alpha MOS α-ASTREE II (Alpha MOS, Toulouse, France) or INSENT SA402B (Intelligent Sensor Technology, Inc., Kanagawa, Japan), which is composed of an autosampler system, an array of sensors, such as a reference electrode, an electronic unit to obtain responses from the sensors and computer software for fingerprint-like analysis, such as principal component analysis (PCA) or partial least square regression (PLSR) (Escuder-Gilabert and Peris, 2010; Alpha MOS, 2021). With different selectivity and sensitivity, potentiometric sensors measure the difference in voltages between the sensor membrane and the reference electrode and then send electric signals to the computer for analysis (de Valle 2017; Jiang et al., 2018; Alpha MOS, 2021).

E-tongue is a promising easy-to-handle instrument and provides results in a rapid time frame at a low cost (Podrażka et al., 2017). This is why e-tongue has been widely used by the food and beverage industry to evaluate product quality and by the pharmaceutical industry to analyze toxic/hazard samples. Consequently, e-tongue has been applied in many different ways in various food and beverage products in many ways. The examples are: 1) to differentiate coffees (Dong et al., 2017) and milk and yogurts (Hruškar et al., 2009); 2) to evaluate storage conditions of melon (Németh et al., 2019); 3) to detect bitterness and astringency of green tea (Zou et al., 2018); 4) to determine rancidity of olive oils (Harzalli et al., 2018); and 5) to evaluate sensory profiles of wines (Kirsanov et al., 2012), Korean fermented soybean paste (doenjang) (Jung et al., 2017), dry-aged beef (Lee et al., 2019), and cheeses (Lipkowitz et al., 2018; Schlossareck and Ross, 2019).

The first concept of the modern e-nose was proposed by Persaud and Dodd (1982), designed to discriminate between various volatile compounds without using highly specialized peripheral receptors. As a new type of electronic nose, the Heracles II e-nose (Alpha MOS) is considered an ultra-fast gas chromatography e-nose, which is composed of three parts: 1) a rapid gas chromatograph specifically designed (odor separation); 2) a hydrogen ion flame detector (volatile compound detection); and 3) a powerful data treatment software (correlations with a sensory panel) (Wojtasik-Kalinowska et al., 2016). Like e-tongue, e-nose has been applied in various studies as it is a rapid tool with robustness and high sensitivity (Cheng et al., 2013; Śliwińska et al., 2016; Li et al., 2019). Another widely used commercial e-nose is PEN3/PEN3.5 (Airsense, Schwerin, Germany). This type of e-nose is equipped with various metal oxide semiconductor (MOS) sensors that have both cross-sensitivity and selectivity, generating response signals to the different volatile compounds.

E-tongue and sensory panel

Relationships between e-tongue analysis and human sensory evaluation have been studied to determine if the e-tongue complements human sensory data and if the e-tongue can be used as an alternative method to sensory panels. Hou et al. (2021) compared three drying techniques [hot air-drying (HAD), vacuum freeze-drying (VFD), and VFD combined with HAD (VFD-HAD)] on flavor profiles of shiitake mushrooms using a potentiometric e-tongue (SA402B, Intelligent Sensor Technology, Inc.) and headspace-gas chromatography-ion mobility spectrometry, FlavourSpec® (G.A.S., Dortmund, Germany) along with a trained panel (n=15). The e-tongue used in this study provided eight basic taste indexes (umami, astringency, saltiness, bitterness, richness, sourness, aftertaste astringency, and aftertaste bitterness) (Li et al., 2019). The trained panel was asked to evaluate the aroma of the samples using the five attributes (i.e., raw mushroom-like, fruity, sweaty, roasted, and seasoning-like) on a 10-point intensity scale (0=absence, 10=highest). The mushroom samples were mixed with 30-mL distilled water and then centrifuged (4,000 rpm, 15 min) to get the supernatant for the e-tongue analysis, which requires a liquid form of samples. The authors found that the e-tongue could be an effective tool to discriminate the overall taste of mushrooms in that fresh samples were located on the right side of PCA, displaying a high relationship to sourness, and dried samples were located on the left side of PCA. Among the dried mushrooms, HAD samples were fully separated from VFD and VFD-HAD, consistent with the descriptive sensory data. The authors also conducted a correlation analysis using Pearson's correlation coefficient to find a relationship between the e-tongue and the human panel. The results indicated that several taste attributes determined by the e-tongue exhibited significant correlations with the aroma attributes determined by the human panel. For example, umami and saltiness negatively correlated with raw mushroom-like attributes, and a positive correlation with sweaty, roasted, and seasoning-like aromas determined by trained panelists. Similarly, there were correlations between "astringency and all aroma attributes" and "sourness and some aroma attributes, including sweaty and seasoning-like aroma". In this study, e-tongue showed significant correlations with the human sensory panel, but the correlations were between taste profiles from the e-tongue and aroma profiles from the sensory panel.

Another study (Gutiérrez-Capitán et al., 2019) investigated the relationship between e-tongue and taste panel to demonstrate that e-tongue can be applied to evaluate sensory attributes of drinking water. They compared the results of the potentiometric e-tongue (with the ion-sensitive field effect transistors-based sensors) with the human taste panel data (n=14) (hedonic evaluation and ranking test) using PLSR. The authors found a significant relationship between instrumental and human sensory data. This significant relationship suggested that the proposed e-tongue could be an effective tool to replace the taste panel when classifying drinking water samples based on their organoleptic characteristics. This study concluded that e-tongue is a more economical, simple, and accessible way to evaluate the sensory properties of drinking water. Furthermore, unlike the human sensory panel, e-tongue can automate the process of drinking water quality evaluation.

Two other studies used a potentiometric e-tongue and compared the e-tongue data with descriptive sensory panel data (Németh et al., 2019; Zhang et al., 2019). Németh et al. (2019) assessed the effects of grafting and storage on the extracted juice of different flesh-colored Cantaloup types (orange and green). They determined the compositional differences between different melon varieties grafted and stored under different conditions and classified their compositional qualities using e-tongue (α-ASTREE II, Alpha MOS) and near-infrared spectroscopy (NIRS) along with a descriptive sensory panel (n=10). Both e-tongue and NIRS are known as rapid tools for qualitative and quantitative food analysis (Hu et al., 2019). NIRS operates within a wavelength range of 700~2,500 nm (Nicolaï et al., 2007), encompassing the emission, absorption, and reflection of light. NIRS analysis depends on the product's chemical composition (microstructure) and its light-scattering properties (Németh et al., 2019). The descriptive panel evaluated the presence of a fermented aroma, sweet aroma, flesh color, texture, juiciness, sweet taste, fermented flavor, aftertaste, and taste persistence according to ISO 13299 standard (ISO, 2003). The authors used multivariate analyses, such as the PCA to describe the main patterns of the variety and storage data set, linear discriminant analysis (LDA) to classify melons according to their varieties and storage conditions, and PLSR to predict sensory parameters from the results of e-tongue and NIRS. They found that both e-tongue and NIRS discriminated orange and green-fleshed melons and predicted in LDA with high accuracies (100%) using both instruments and classified different storage conditions of melons with high accuracies. The results showed that the e-tongue was more sensible than the human sensory panel when discriminating the different types of melon and varieties of the same type. For example, the descriptive panel only found the differences in fermented taste and aroma among the different varieties of the same type of melon. Still, e-tongue data discriminated against those with high accuracy. Overall, the results of both e-tongue and NIRS complemented descriptive sensory panel data, but the e-tongue was found to predict storage and standard analytical parameters better than NIRS. However, the authors recommend combining both methods to provide a rapid, non-destructible way to monitor varieties and the effect of storage on the quality of Cantaloupe, as NIRS showed higher classification accuracies.

Zhang et al. (2019) used a potentiometric e-tongue and a descriptive sensory panel to investigate the overall taste profiles of chicken soup and soy sauce in the presence/absence of novel umami peptides from peanut protein isolate hydrolysate. The e-tongue used in this study was TS-5000Z (Intelligent Sensor Technology, Inc.) equipped with five sensors indicating five taste qualities (sweetness, bitterness, saltiness, umami, astringency). Then, two taste qualities (aftertaste-bitterness, and aftertaste-astringency) were immediately measured after cleaning the sensors to detect the substances that were still absorbed by the sensors' lipid membrane (Toko, 2000; Toelstede et al., 2009). In this study, the detection of umami and astringency in chicken soup and soy sauce by the e-tongue and the trained panel was similar. However, it was found that the responses of e-tongue sensors were much more sensitive than the human tongue in terms of the recognition of bitterness and saltiness. The authors concluded that the e-tongue could replace a human sensory panel for taste assessment to estimate the taste profiles of foods rich in peptides.

Several studies utilized the e-tongue and human panels and compared the ability to determine taste profiles between the e-tongue and the panel without statistical correlation analysis (Yang et al., 2019; Paup et al., 2021; Fan et al., 2022; Wang et al., 2022a, b; Zhang et al., 2023). Among these studies, two studies, Paup et al. (2021) and Fan et al. (2022), used the Alpha MOS e-tongue (α-ASTREE II) to compare the e-tongue data with human panel data. Paup et al. (2021) utilized the e-tongue to detect changes in sensory properties in red wine (Merlot) after the inoculation of spoilage microorganisms over time and compared the e-tongue with flash profiling (FP) using a sensory panel (n=7). This was to determine whether the wine industry could use an e-tongue to detect wine faults early. A trained/experienced sensory panel in FP identifies sensory attributes that best describe the differences among samples. They were also asked to rank the samples for each attribute they selected. In this study, the FP panel was asked to evaluate twelve wine samples in each of the total seven sessions [Day 0 (immediately after inoculation) and following weekly evaluation for 42 days] to find the aroma attributes that best differentiate all twelve wine samples. They were also asked to rank the samples from the lowest to the highest intensities of those identified attributes. The e-tongue successfully differentiated the wine faults elicited by different spoilage microorganisms starting at Day 21 of storage at 23°C, but the human sensory panel started discriminating the faulted wines starting at Day 28. Additionally, the results from the FP did not show a significant increase in traditional spoilage descriptive attributes, including dairy, fermentation, earthy, chemical/solvent, rotten and putrid, animal, savory, and veggie from the *Brettanomyces* aroma wheel (Joseph et al., 2017) until Day 42. This study's results suggest that e-tongue can detect changes in aroma attributes in faulted wines based on their taste (non-volatiles) profiles before a trained sensory panel detects wine faults in the aroma profile (volatiles) profiles. The authors suggest that the wine industry limits the financial losses due to wine faults using e-tongue, which enables early detection of sensory changes in faulted wines. Another study (Fan et al., 2022) used the e-tongue to investigate the taste quality of gonads of Chinese mitten crabs (*Eriocheir sinesis*) during the 8-week frozen storage period at −20°C, −40°C, and −80°C. The authors also compared the e-tongue data with a descriptive sensory analysis using a trained panel (n=8). The panel evaluated the intensity of the samples' umami, sweet, bitter, and salty taste. The e-tongue successfully distinguished the taste profiles of samples stored at different temperatures on the taste map. Even though the authors did not use statistics to correlate the e-tongue data with the sensory panel data, the samples stored at −80°C, which was found to be the best storage temperature for gonads from this study, were close to the control (sample stored for two weeks) or were grouped (samples stored for 4, 6, and 8 weeks). This shows that e-tongue can serve as an effective tool for predicting the taste profiles of gonads samples.

E-nose and sensory panel

Similar to the e-tongue, many researchers have performed the e-nose analysis and attempted to correlate it with the human sensory panel. Table 1 summarizes the reviewed studies that used either an ultra-fast gas chromatography e-nose (Heracles II, Alpha MOS) or a commercial e-nose containing MOS (FOX3000 or FOX4000, Alpha MOS; PEN3 or PEN3.5, Airsense). A few studies used a lab-made e-nose, which correlates well with human sensory panel data (Chen et al., 2019; Huang et al., 2019).

Rottiers et al. (2019) used gas chromatography-based e-nose (ultra-fast gas chromatography, Heracles II, Alpha MOS) to characterize and compare the flavor profiles of cocoa cultivars and to investigate the genotype effects on the flavor attributes. The authors also used gas chromatography-mass spectrometry (GC-MS) and descriptive sensory analysis using a trained panel (n=12). E-nose

Table 1. Examples of recent e-nose applications and comparisons with sensory evaluation

E-nose	Sensor array	Application	Sensory evaluation	Statistic	Reference
Heracles II, Alpha MOS	MS based method	Flavor comparison of cocoa cultivars	Descriptive sensory analysis (n=12)	PCA, PLSR	Rottiers et al., 2019
		Sensory quality evaluation of parenica cheese	Acceptance test (n=169)	PCA	Štefániková et al., 2020
FOX2000, Alpha MOS	6 MOS	Changes in aroma profiles of oyster during storage	Preference tests Non-trained panel (n=19)	PCA, correlation	Kawabe et al., 2019
FOX4000, Alpha MOS	18 MOS	Sensory changes in gluten-free oat biscuits during storage	Descriptive sensory analysis (n=10)	PCA	Duta et al., 2019
		Suitability of tea cultivars for processing oolong tea	Aroma quality by experts (n=3)/ acceptance by consumers (n=63)	PCA, correlation	He et al., 2022
PEN3.5, Intelligent	10 MOS	Evaluation of aroma characteristics of sugarcane juice	Triangle test (n=36)	PCA, LDA, PLSR	Wang et al., 2019
Lab made	10 MOS	Freshness evaluation of meats	Freshness sensory evaluation (experienced assessors, n=18)	PCA, DFA	Chen et al., 2019
	7 MOS	Detection of freshness quality of spinach	Descriptive sensory analysis (n=10)	SVL model	Huang et al., 2019

MS, mass spectrometry; MOS, metal oxide semiconductor; PCA, principal component analysis; PLSR, partial least square regression; LDA, linear discriminant analysis; DFA, discriminant factor analysis; SVL, support vector machine.

could discriminate all cocoa liquors, with two cultivars mostly close to each other on the PCA map, meaning that these two cultivars have similar odors. The result was consistent with the trained panel work. With the similarity between PCA conducted on e-nose and sensory data, the authors reported that e-tongue could be a powerful tool for rapidly assessing cocoa liquor flavor profiles. The authors suggested that the e-nose can be further trained with additional samples with known sensory scores. Then, the e-nose will be applicable to predict the sensory profiles of unknown samples using PLS models built in the Alpha MOS software. Another study (Štefániková et al., 2020) also used the ultra-fast gas chromatography e-nose (Heracles II) to compare the e-nose system with consumer acceptance to evaluate the quality of *parenica* cheese (a traditional Slovak steamed cheese). The authors used 192 cheese samples to evaluate the sensory characteristics using the e-nose. A total of 169 untrained panelists were divided into 16 groups (10～13 panelists/group) and were asked to evaluate the color and cheese aroma intensity of cheese samples. The PCA was conducted to visually map the samples based on how the aroma profiles change in certain months of cheese production (February～April, June, and September～December). The results showed that a combination of the e-nose and e-eye appeared to be a more objective tool for sensory characterization and quality assessment of the cheese samples in the routine analysis, not a short period. The electronic system appeared to be an appropriate complement to the sensory evaluation. However, no statistics were conducted to analyze the correlations statistically.

Another study (Chen et al., 2019) compared the lab-made e-nose and human sensory evaluation and concluded that the e-nose is a promising tool for detecting meat freshness. The e-nose equipped with 10-MOS sensors was developed by the authors. These sensors were selected based on their sensitivity to specific volatile compounds. The trained sensory panel in this study consisted of 18 experienced panelists and evaluated known samples after 2-week training and then evaluated unknown meat samples (pork, beef, and mutton) for color, odor, and texture. They were also tasked to divide the samples into three groups: fresh, sub-fresh, and putrid. They used PCA to analyze the characteristic values to investigate the differences between samples subjected to different storage times and discriminant factor analysis (DFA) to generate a database of the three categories of meats based on their freshness status. All three meat samples (pork, beef, and mutton) with different storage times detected by e-nose well distinguished the meats with varying times of storage. Using sensory evaluation data as a reference, the DFA showed that the e-nose could not only distinguish but also judge the freshness of the samples during seven days of storage time. Therefore, the authors suggest that the e-nose can detect different freshness levels of the meat samples. Huang et al. (2019) also developed an e-nose equipped with seven MOS sensors (Figaro Co., Ltd., Osaka, Japan) to investigate the feasibility of the e-nose with computer vision in detecting spinach freshness and edibility. These novel technologies would be an effective and powerful method for rapidly detecting spinach quality, which is highly perishable.

A recent study by He et al. (2022) distinguished different oolong tea cultivars. They correlated the e-nose data (FOX4000, Alpha MOS) and GC-MS with a headspace-solid phase microextraction method (HS-SPME-GC-MS) to explore the differences in aroma compounds and their effects on oolong tea cultivars suitability. The instrumental data (e-nose and HS-SPME-GC-MS) were compared with the aroma profiles evaluated by three tea experts and the acceptability of the tea samples acquired by 63 tea consumers using correlation analysis. The e-nose results showed significant differences ($P<0.05$) between the different tea cultivars samples. The e-nose data were consistent with the human sensory data, reflecting the accuracy of the e-nose detection and implying a close relationship between the e-nose and human sensory data. However, it was found that with HS-SPME-GC-MS, the e-nose data showed stronger correlations with human sensory panel data than the e-nose alone. This study concluded that a combination of e-nose and HS-SPME-GC-MS could explain expert review and consumer acceptance evaluation scores. However, the authors did not suggest that human sensory work can be replaced by e-nose and HS-SPME-GC-MS. Duta et al. (2019) also used FOX4000 e-nose to monitor changes in odor profiles due to oxidation during storage at room temperature (up to 90 days in different types of packaging materials under light and darkness conditions) of the gluten-free (GF) oat biscuits. The authors used a descriptive sensory panel (n=10) to analyze GF oat biscuits after 30 days, 60 days, and 90 days under light and dark conditions. The trained panel evaluated the biscuits based on the surface color, smell and taste, crunchiness at the first bite, and off-flavor using a 5-point scale (1=not identified; 5=very strong). E-nose well distinguished the biscuit samples stored under different conditions (light or dark) for an extended period of storage time (30, 60, and 90 days). PCA was conducted to detect the differences in the odor profiles of the biscuit samples. It was found that the e-nose results were consistent with trained panel data. For example, the samples stored for 90 days under light conditions were located far from the other samples on the PCA plot, showing distinct odor profiles. The trained panelists also found these two samples with higher scores for off-flavor. There was another study that investigated the changes in odor profiles of living oysters with shells (*Crassostrea gigas*) under different air-exposed storage conditions (5°C and 20°C for seven days) (Kawabe et al., 2019). The authors used Alpha Fox2000 equipped with six MOS sensors (Alpha MOS) and a headspace autosampler. Nineteen non-trained panelists were also used to evaluate odors (seashore and oily) and its preference. This study found that the e-nose performed better in detecting differences in oyster odors during the first five days of storage as the panel was unable to detect any differences. The e-nose revealed that living oysters during the 7-day air-exposed storage would cause odor deterioration even at a refrigerated temperature (5°C). This study suggested that the e-nose system can be used to monitor the oysters' quality change.

A study compared e-nose and a discrimination test (i.e., triangle test) (Wang et al., 2019) to investigate the aroma profiles of sugarcane juice using e-nose (PEN3.5, Airsense). This study conducted PCA and LDA of e-nose data and triangle sensory tests. The authors concluded that e-nose analysis with GC-MS volatile compound data would monitor the sensory quality change, especially the smell and/or to identify the source of feed of sugarcane juice processing.

Applications of both e-tongue and e-nose in sensory evaluation

Some studies have used both e-tongue and e-nose and compared them with human sensory data. Jiang et al. (2021) used a potentiometric e-tongue (α-ASTREE II, Alpha MOS) equipped with seven working electrodes with one reference electrode (Ag/AgCl) and SuperNose e-nose (Isenso Intelligent, Shanghai, China) equipped with an array of 14-MOS sensors to analyze the headspace of dry-cured hams. They also used computer vision with the e-senses to acquire image information on different dry-cured ham samples. Quantitative descriptive analysis was conducted to analyze sensory characteristics such as odor, taste, and appearance of the samples with different aging times. The trained panel (n=11) evaluated 12 sensory attributes, including fermented odor, cheese odor, fat rancid odor, smoky odor, meaty odor, sour odor, and butter odor. The authors used Pearson correlation to analyze the correlations among intelligent sensory technologies (e-tongue, e-nose, computer vision) and found small correlations with each other. The PCA biplots visualize the data of the e-tongue and e-nose and show three well-separated groups of the hams with different aging times of 1 to 3 years for the e-nose but not the e-tongue. The descriptive sensory analysis had seven odor-related attributes and five significantly different among the aging groups, which complemented the e-nose data. The authors built the prediction models of quality indices, such as the aging time and sensory attributes based on computer vision, e-tongue, and e-nose. They concluded that the prediction model applying 27 features obtained from multiple intelligent sensory technologies (e-tongue, e-nose, and computer vision) with a high classification accuracy rate (100%) could predict the sensory attributes of the dry-cured ham.

The study by Aguinaga Bósquez et al. (2021) evaluated the sensory attributes of eggs produced by hens fed with different diets developed using different doses of a brewery byproduct enriched with organic zinc (Control 0%, 2.5%, and 5%) as feed supplements. They used a sensory panel, e-tongue, and e-nose for the sensory quality assessment. The sensory evaluation used five trained panelists who analyzed sensory attributes based on an intensity scale of 0 to 9 points. Twenty-one sensorial characteristics for raw eggs, boiled eggs, and fried eggs were evaluated. In this study, the e-tongue analysis (α-ASTREE II, Alpha MOS) needed unique sample preparation of the eggs, different from other liquid or solid samples. The eggs were crushed and beaten for 1 min, and 2 g of the homogenized egg were mixed with 98 mL of distilled water. E-nose analysis (Heracles NEO, Alpha MOS) is designed for quick volatile analysis, and thus, it is considered an ultra-fast gas chromatography comprising two columns. The sensory evaluation did not show any significant differences in the sensory attributes of the eggs. However, using LDA, the e-tongue could differentiate the three sample groups with relatively high prediction accuracy (60.5%). Using the PCA-discriminant analysis, the e-nose data showed that the three sample groups were distinguished with 65.4% accuracy. The authors concluded that laying hens' feed supplements with the industrial byproduct would not affect the eggs' sensory characteristics. Still, advanced analytical methods, including the e-tongue and e-nose, can detect the feed supplements' effect. The authors suggested that a complex methodology, including human sensory analysis and e-tongue and e-nose, should be used to determine the egg quality's effect.

The powder form of kimchi, traditional fermented Korean food prepared with vegetables and spices (garlic and pepper powder), was analyzed to determine physicochemical characteristics, aroma profiles, and sensory characteristics (Park et al., 2018) using e-nose (Heracles II, Alpha MOS), e-tongue (α-ASTREE II, Alpha MOS), and sensory evaluation. For the sensory evaluation, 15 experienced panelists were asked to evaluate the overall quality, appearance, flavor, and taste using the 7-point Likert scale. Both e-tongue and e-nose analyses demonstrated statistically significant differences among samples based on the different drying temperatures [high (~60°C) vs. low (~35°C)]. The results of the sensory evaluation showed that the flavor and taste were rated the highest for the kimchi powder prepared using HAD at high temperature compared to the other drying methods such as freeze drying, decompression drying (DD) at high temperature, HAD at high temperature, DD at low temperature and HAD at low temperature. The PCA biplots of e-tongue and e-nose showed that the kimchi before drying could be distinguished from kimchi powder based on taste and smell, respectively. It was also found that the freeze-dried kimchi differed from other drying methods, such as HAD and DD, either using hot or low drying temperatures. However, the samples' taste or odor quality was mainly affected by the drying methods but not the drying temperatures. The sensory results were reliable because they were consistent with the electronic tongue and nose results.

Liu et al. (2022a) explored the effects of five different sterilization methods (pasteurization, back-pressure sterilization, high-temperature short-term sterilization, membrane filtration treatment, and high-pressure processing) on the flavor of cold brew coffee. The authors used an ultra-fast e-nose (Heracles NEO, Alpha MOS) and e-tongue (TS-5000, Insent, Atsugi, Japan) to analyze the aroma and taste characteristics of coffee with descriptive sensory analysis. The results showed that the non-heat sterilization was more favorable to coffee's sensory attributes than heat sterilization in that non-heat sterilization retained the aroma and taste of cold brew coffee. From the e-nose and e-tongue results, the authors found significant differences among the five sterilization methods: 1) back pressure sterilization showed a significant negative effect on coffee flavor as total aroma decreased and sourness, bitterness, and astringency increased; and 2) among the heat sterilization, high-temperature short-time sterilization is more suitable resulting to processing and production with reasonable production cost as well as well-retained sensory quality. However, the sensory evaluation did not show any significant differences in the scores of flavor, aftertaste, acidity, and body among the samples. The human sensory panel did not detect any significant differences, unlike the e-nose and e-tongue. The authors did not make any correlation between the electronic system with the human panel data, but the electronic system could detect subtle differences among the cold brew coffee samples, which might not be detected by human panels.

Trabelsi et al. (2021) used flavored olive oils (FOOs) as natural additives to ensure food safety and product quality during the marinating process of anchovy filets to achieve more sustainable production. The authors used: 1) a mixture of parsley, fresh garlic, and lemon (Mix-FOO) and 2) cumin FOOs (Cm-FOO). Sensory quality parameters of the samples were determined using e-tongue (α-ASTREE II), e-nose (FOX 4000), and e-eye (Iris Visual Analyzer 400), which are all manufactured by Alpha MOS. The e-tongue was equipped with seven sensors specifically designed for food and beverage analysis with an Ag/AgCl reference electrode. The e-nose was equipped with an array of 18-MOS gas sensors, whose resistance is modulated in the presence of a target gas or vapor, combined with an automatic headspace sampler HS100. Finally, the e-eye is a computer vision system. Along with the e-sense system, sensory acceptability (odor, appearance, taste, and overall acceptance on a 9-point hedonic scale) was also determined using a human panel (n=20). All three e-sensing evaluations are shown in the PCA plots. The e-tongue results showed that Mix-FOO and Cm-FOO samples had less variation in taste profile during storage (14 days) compared with control samples. The e-nose showed that the odor profiles of the control and two FOO-treated samples changed during storage. For color stability, Cm-FOO samples had the highest stability over the 14 days storage time compared with the Mix-FOO and control. The authors did not correlate the e-sensing data with sensory data using a human panel, but the sensory results were comparable to the e-sense system, confirming that the e-tongue, e-nose, and e-eye can be used to analyze the marinated anchovies. The interesting results were, however, the overall acceptance ratings of the control and the two FOO-treated marinated anchovies with no significant differences over time, even though significant differences in color and taste were observed among the samples.

Unlike most of the studies mentioned in this review, the study by Liu et al. (2022b) concluded that e-sense data (e-tongue and e-nose) with the e-eye seemed inadequate to explain the taste and smell liking scores of the six samples that investigated the effect of different levels of L-arabinose addition (0.5～5%) on the sensory characteristics of fish (silver carp) sausage. E-tongue and e-nose were used to compare the taste and aroma profiles of silver carp sausage samples by adding L-arabinose. The sausage samples (4 g) were homogenized, placed in a 10-mL headspace vial, and then incubated at 60°C for 15 min before injection into the e-nose. For the e-tongue analysis, 2-g samples were homogenized with 15-mL deionized water using an FM-200 homogenizer (Shanghai Fokker Equipment Co., Ltd., Shanghai, China). After 30 min at room temperature, samples were centrifuged, and the supernatant was transferred and diluted to a constant volume of 100 mL. Fifteen panelists were asked to evaluate the samples' color, texture, taste, smell, and overall acceptability on a 9-point hedonic scale. Both e-tongue and e-nose PCA results showed that L-arabinose enhanced the aroma and taste profiles. The sensory panel rated the highest overall acceptability for the fish sausage with 2% L-arabinose. No attempt was made to correlate the e-sense data with the sensory panel acceptance data. The PCA results from the e-tongue and e-nose analyses appeared to cluster the six samples into a few groups based on similar aroma and taste profiles. However, those e-sense data sufficiently explained the taste and smell liking scores of the six samples.

Kvass, a low-alcohol traditional fermented beverage produced from barley malt with complex microbial flora (*Lacticaseibacillus paracasei*, *Acetobacter pasteurianus*, and *Saccharomyces cerevisiae*), was produced (novel kvass) and compared with the commercial kvass (produced from bread kvass) (Wang et al., 2022b). They were characterized by e-tongue, e-nose, and descriptive trained panel, along with of physicochemical and probiotic properties. An e-tongue (α-ASTREE II, Alpha MOS) was used to evaluate the taste profiles of the samples. An e-nose (PEN3, Airsense) equipped with ten built-in MOS gas sensors was used to collect odor profiles of the Kvass samples. The trained panel (n=10) was used to evaluate the appearance, aroma, and taste on a 100-mm line scale. Using response surface methodology, the trained panel results were used to determine the optimal fermentation parameters for kvass (wort concentration, fermentation time, and fermentation temperature). With the optimal fermentation conditions, the authors produced kvass, collected primary fermentation products (after adding starter culture) and second fermentation products (after adding honey and white sugar), and compared them with commercial kvass (traditional kvass). The e-tongue results produced in the PCA biplot (PC1: 76.9% and PC2: 21.9%) showed a clear distinguishment between lab-made kvass *vs*. commercial products. Similarly, the PCA biplot from the e-nose results had more than 90% accumulative variance contribution rate of the first two principal components, meaning that the two PCs could reflect all the characteristics of the volatile odor of different kvass samples. The novel and traditional kvass were well separated on the e-nose PCA biplot. From the e-sense system, the authors concluded that novel kvass was found to show better taste, but no sensory data supported this.

To understand what factors affect the overall acceptability of roasted sweet potatoes were collected, roasted, and then analyzed for color, amino acids, sugar composition, and flavor (Hou et al., 2020). For the flavor characteristics, the e-tongue (α-ASTREE II, Alpha MOS) is equipped with saltiness (STS), sourness (SRS), umami (UMS), metallic (GPS), bitterness (BRS), sweetness (SWS), and spiciness (SPS); the rest of the unidentified sensors are to detect sweetness and bitterness. An e-nose (PEN3.5, Airsense) with a sensory array of 10 sensors was conducted, along with consumer acceptability testing (n=26). Untrained consumers were asked to evaluate the samples' overall acceptability, color, odor, moisture, hardness, sweetness, and ease of swallowing using a 9-point hedonic scale ranging from 1=dislike extremely to 9=like extremely. Correlation analysis was conducted to determine the importance of the factors in the overall acceptability. The PCA biplot from the e-nose showed the differences in the aroma among the samples. Three cultivars were well separated from the other samples, but the volatile compounds in these three cultivars were very different, while the other eight cultivars showed similar volatile compounds. The e-tongue results showed that roasted sweet potatoes had the highest response to STS, followed by UMS and four comprehensive sensors (BRS, SWS, GPS and SPS), and SRS. There were well separated three groups identified in the e-tongue PCA biplot. The authors did not correlate the sensory data with either e-nose or e-tongue. Still, they mentioned that the sensory evaluation results were similar to that of the e-tongue, showing that the most liked and the least liked samples by the human panel were significantly different in the e-tongue results and the two cultivars, which showed similar taste profiles had similar acceptability from the consumer testing.

Lao et al. (2020) studied the effects of enzymatic hydrolysis (celluase and pectinase) and fermentation on the flavor and taste of *Cordyceps militaris* fermented beverages. E-nose, e-tongue, and sensory analysis were conducted for flavor and taste evaluation. E-nose (iNose, Ruifen Trading Co., Ltd., Shanghai, China) equipped with 14-MOS gas sensors (having different response values to different smells) was used to distinguish the volatile compounds of fermented beverages. E-tongue (SA402B, Intelligent Sensor Technology, Inc.) equipped with eight taste membranes, representing the taste of sourness, bitterness, bitter aftertaste, astringency, umami, richness, and saltiness was used to evaluate the taste of the beverages. A trained panel (n=7) was used to evaluate the appearance, aroma, sweetness, sourness, and consistency of the beverages. The effect of the fermentation process and enzymatic hydrolysis on the aroma was measured using an e-nose. The e-nose results confirmed that the sample fermented for 60 h had the maximum response value compared to the 0, 12, 24, 36, and 48 h fermentation, and the 60 h fermentation beverage was well separated from the control and all other fermentation times. However, the different enzymatic hydrolysis samples (3:2, 1:1, 2:3 cellulase/pectinase) were much closer to each other and separated from the control, indicating a smaller odor difference among the enzymatic hydrolysis samples. E-tongue can convert electrical signals into taste signals to evaluate the taste profiles of fermented beverages, which have a small threshold of sensation and can well exclude the subjectivity of sensory evaluation (Jiang et al., 2018).

It was found that four sensors were more sensitive to the fermented beverages, two of which responded to the aromatic compounds (more pleasant aroma). E-tongue results showed that the sourness of the fermentation increased, and bitterness decreased with the fermentation time prolonged. The authors believe that the reduction in bitterness may be due to forming other compounds, such as acids, that can mask other tastes. Furthermore, the effect of different enzymatic hydrolysis pretreatments on the beverage taste was observed. The enzymatic hydrolysis treatments had some effects on the fermented beverages' sourness, bitterness, and astringency. The maximum difference in response values of sourness, bitterness, and astringency of the beverages, but the PCA plot showed that all samples with different ratios of cellulase/pectinase were overlapped, representing that the enzymatic hydrolysis has little effect on the taste of the fermented drink. Human panel analysis also showed that the aroma scores were higher in the enzymatic group than that in the control group, and the highest scores were obtained and cellulase/pectinase with a 1:1 ratio. E-tongue, e-nose, and sensory results confirmed that the beverages' flavor was enhanced by enzymatic hydrolysis.

FUTURE TRENDS/PROJECTIONS

Through instrumental sensory evaluation, e-senses (e-tongue and e-nose) are presently used in the food and beverage industry to monitor product quality in the quality assurance/quality control department. It is expected that commercial e-tongue and e-nose will soon be able to operate online for real-time detection of off-odors and off-tastes in a live production/processing line. This way, the e-tongue and e-nose will be effectively integrated into food processing and production for real-time quality control and assurance purposes. With the advent of biological sensors and material specificity to certain compounds, these sensory instruments have tremendous potential to be implemented in the harvesting of fruits/vegetables along with post-harvest and horticulture technologies. For example, further advancements in e-nose technologies might be able to predict the harvest period of fruits (such as different types of berries) and vegetables with the help of deep learning or machine learning algorithms and advanced regression models.

These instruments can also have potential uses in predicting the shelf-life of foods. Presently, several studies have focused on correlating the instrumental sensory data (i.e., e-tongue and e-nose data) with human sensory scores through advanced predictive modeling of deep and/or machine learning approaches. This trend will eventually lead to the development of e-tongue and e-nose technologies to reliably predict the human sensory scores of a particular food product by analyzing the products' odor and taste profiles. This development will also enable the food industry to ensure the sensory satisfaction of their products to the consumers/customers with much-coveted revenues.

The instrumental sensory capabilities of future e-tongue and e-nose may also develop revolutionary decision-making strategies in the packaging industry in particular. In an ever-warming world, all packaging companies would conduct extensive research on sustainable packaging solutions. However, the typical odors prevalent are a major hurdle in recyclable, sustainable packaging solutions. Future advancement of e-nose technologies and their potential integration in real-time packaging production lines may help with the quality control and assurance of sustainable packaging materials by eliminating unwanted odors offensive to the human sense of smell.

The e-tongue and e-nose can be used in breeding programs. Few breeding programs evaluate the sensory quality because of the time and cost constraints in using human sensory panels, even though it is essential to determine flavor profiles of the breeding lines to select the desirable lines in the breeding programs. As e-tongue and e-nose are rapid tools to determine taste and aroma profiles compared with human sensory panels and promising correlations with human sensory panel data from previous studies, these instruments have a great potential for quick flavor discrimination in breeding programs.

By implementing these advanced data analysis techniques and predictive modeling, it is expected that e-tongue and e-nose technologies will be perfected shortly to completely replace or at least be a viable alternative with the time-consuming and often-skewed human sensory panel in the field of sensory evaluation. As these instrumental sensory technologies are becoming the hot topic of engineering research, we can expect that future e-tongue and e-nose devices will be portable and much cheaper than they are now. Evolving development of e-nose and e-tongue technologies may enable the next generation to conduct rapid food safety analysis and quality detection in a coming era when the luxury of food abundance will not be an option for them as we have experienced in our lifetime.

LIMITATION

The authors believe that the biggest hurdle in developing multiple intelligent sensory technologies is the engineering of materials to be used in chemiresistive electrodes and sensors that shows sensitivity and specificity to certain compounds to obtain data that can be interpreted in terms of sensory analysis. However, several studies have currently been conducted to engineer such sensor materials so that the e-tongue and e-nose can be cost-effectively produced with advanced technology. To operate these instruments, skilled personnel are often required for e-tongue and e-nose analysis to obtain reliable data that can be translated and interpreted in the language of sensory evaluation. Developing, calibrating, and optimizing proper analytical methods for each type of food is also a time-consuming and tedious approach that is typical of all commercially available models of e-noses and e-tongues. However, ongoing research to incorporate deep/machine learning in e-nose and e-tongue data analysis and interpretation may one day pave the way for more automation for operating these sensory instruments.

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The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Concept and Design, Analysis and Interpretation, Data collection, Writing: all authors. Critical revision of the article: SC. Final approval of the article: all authors. Overall responsibility: SC.

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