The development of sensory analysis techniques in the food industry and the research progress

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The development of sensory analysis techniques in the food industry and the research progress

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Abstract. Sensory analysis plays a crucial role in the food industry, serving as an essential tool in product development, quality control, and consumer research. It involves evaluating the sensory attributes of food products-taste, aroma, texture, and appearance. Although human-based sensory evaluation is widely used and relatively developed, it is likely to be affected by subjective issues. Moreover, the result of sensory evaluation is difficult to standardize and quantify. To address this, instrumental analysis methods have been introduced to establish correlations between the chemical composition or physical properties of food and the outcomes of sensory evaluation. However, the data generated from instrumental analysis are often large and complex. To link these data with sensory evaluation results, chemometric methods are employed for analysis. With advancements in technology, more cutting-edge tools, such as electronic noses and electronic tongues, have been applied to sensory analysis. Due to their rapid assessment and ability to detect multiple indicators, these technologies are becoming increasingly popular in industrial applications.

Keywords: Sensory analysis, Instrumental analysis, Chemometric, Electronic nose, electronic tongue.

1. Introduction

With the development of the food industry, both companies and consumers have raised their expectations for product quality and taste. Sensory analysis plays a crucial role in the food industry, with its applications including several key stages of production. During the product development phase, sensory analysis supports the creation of innovative flavors, helping to develop products with a competitive edge in the market. In the production process, sensory analysis is employed for quality control to ensure consistency across batches. In consumer research, sensory analysis effectively captures consumer preferences and demands, providing valuable feedback to companies. Overall, sensory analysis offers scientific guidance for various stages of food production. Food sensory analysis is a discipline that evaluates five sensory attributes of food-vision, olfaction, tactile, gustation, and auditory perception to assess product quality.

Sensory analysis plays a crucial role in the food industry, serving as an essential tool in product development, quality control, and consumer research. It involves evaluating the sensory attributes of food products-such as taste, aroma, texture, and appearance.

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Traditional sensory analysis methods can be roughly categorized into two types: sensory evaluation techniques that rely on human senses and instrumental analysis techniques that assess specific chemical or physical properties of food using analytical instruments [1].

To a large extent, traditional sensory evaluation methods primarily rely on human sensory organs to evaluate multiple sensory attributes comprehensively. These methods assess the quality and acceptability of products based on established criteria. However, due to these evaluations depend on the human senses including olfactory, gustatory, auditory, tactile, and visual senses, the sensory experiences inevitably interact and affect each other [2]. Moreover, the results are significantly affected by the individual factors of the panelists participating in the tests. The design of the testing environment, along with individual differences among participants (lifestyle, background, ethnicity, and age) further impact the outcomes of sensory evaluation [3]. Consequently, the results of sensory evaluation tend to be unstable and have low reproducibility.

To address these challenges, sensory evaluation techniques that rely on human senses require well-designed experiments, strict control of the testing process and participants, and appropriate interpretation of the results [4]. These measures are essential to obtain accurate and reliable outcomes in sensory evaluation.

Due to the stringent requirements and various limitations associated with traditional sensory evaluation techniques that rely on human senses, instrumental analysis methods have increasingly become a vital component of sensory analysis. These methods offer the advantages of quantitative detection, along with a faster and more convenient testing process.

Instrumental analysis techniques evaluate food flavor by analyzing volatile flavor compounds, as well as physical properties such as color and texture. These methods provide an objective and quantitative assessment of food quality by measuring specific chemical and physical attributes related to sensory experience.

In the food industry, instrumental techniques that commonly used for analyzing flavor compounds include gas chromatography (GC), gas chromatography-mass spectrometry (GC-MS), and high-performance liquid chromatography (HPLC), etc. Together, these techniques provide a comprehensive understanding of the complex chemical makeup of food flavors, contributing to product development, quality control, and food safety efforts across the industry.

Despite the advantages of instrumental analysis techniques, they have several limitations. One of the most significant limitations is their limited scope. These methods typically focus on analyzing specific chemical or physical properties, such as volatile compounds or physical texture, without considering the complexity of human perception. As well known, human sensory evaluation involves the description of complex interactions between multiple sensory perceptions, which instrumental techniques are unable to interpret such complex data [5].

Another major limitation is the lack of correlation with human perception. While instrumental analysis methods provide objective and quantitative data, these results do not relevant with any sensory experiences of humans. Instruments can detect certain chemical components, but human perception is influenced by a combination of sensory factors, which instruments cannot measure. As a result, instrumental analysis techniques still rely on human sensory evaluation to interpret the data, ensuring that the results reflect actual sensory experiences [5].

This article begins by exploring traditional instrumental analysis techniques used in food science, presenting an overview of commonly used methods while comparing their differences, advantages, and limitations. As technology develops, a growing number of emerging techniques, such as electronic noses, electronic tongues, artificial intelligence, and machine learning algorithms, have been introduced into sensory analysis. These innovations are driving the development of sensory analysis technologies toward becoming more comprehensive, accurate, and efficient.

2. Overview of instrumental methods in sensory analysis

In sensory analysis, food-related attributes are associated with the five senses: vision, smell, taste, touch, and hearing. These five senses interact and influence one another, together shaping the sensory

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perception of food. Regardless of the sensory analysis method used, the measured parameters inevitably correspond to one or more of these senses. Attributes related to smell and taste are primarily linked to the chemical composition of compounds, such as the correlation between volatile compounds and aroma. On the other hand, attributes related to vision, touch, and hearing are associated with the physical properties of food, such as the rheological characteristics of liquid foods. Therefore, instrumental methods applied in the food industry can generally be classified into two categories: those that measure the chemical composition of food and those that evaluate its physical properties.

Although sensory evaluation is a commonly used method in product development and quality control, and its application in the food industry is fully developed. However, the outcomes are often subjective, and the data obtained can be difficult to quantify. To address these challenges, researchers have focused on minimizing the drawbacks of sensory evaluation. One approach is to combine instrumental analysis data with human sensory evaluation results, analyzing the correlation between these two sets of data. This method produces more objective results that are easier to quantify and standardize, leading to its widespread use in the food industry.

Table 1 summarizes several common instrumental sensory analysis techniques and their applications. The data obtained from these instruments do not have a direct correlation with human sensory experiences. In order to get meaningful results, the instrumental data must be compared with sensory evaluation outcomes, establishing a relationship between the two in order to interpret the results.

Table 1. Summary of applications of instrumental sensory analysis techniques.

Samples	Instrumental methods	Objectives	Reference
Yogurt	SPME–GC–MS	Profiling and modeling the major volatile compounds contributing to unsatisfactory sensory characteristics in different types of yogurts.	[6]
Honey	GC–MS	Establish the relationship between sensory attributes of honey and the types of volatile compound.	[7]
Baijiu	SPME–GC–HPLC	Identify the key aldehydes, alcohols, and acids responsible for the pungent sensory attribute by comparing sensory evaluation data with HPLC and GC data.	[8]
Cherry Wines	GC–MS, GC–O	Identify the key ester aroma compounds in cherry wine and study the correlation between aroma intensity and aromatic compounds.	[9]
Bread	Texture Analyzer	Quantitatively study the staling process of bread as storage time increases.	[10]
Liquid and Semisolid Food	Rheometer	Establish the relationship between rheological properties and sensory attributes of various liquid and semisolid food samples.	[11]
Hazelnut	Colorimeter	Model the relationship between baking temperature and color changes in hazelnuts and establish a connection with sensory evaluations.	[12]

Note: SPME, solid phase micro-extraction; GC, gas chromatography; MS, mass spectrometry; HPLC, high-performance liquid chromatography; GC–O, Gas Chromatography-Olfactory Port

In industrial applications, only quantitative results from sensory analysis can provide specific guidance for product development, levels grading, and quality control. For example, Gao et al. analyzed several key chemical compounds in different grades of Pu-erh tea using high-performance liquid chromatography, indicating the concentrations of these compounds for each grade [13]. To mathematically model the relationship between instrumental analysis data and sensory evaluation outcomes in order to get quantifiable sensory analysis results, chemometrics is essential.

Chemometrics applies theories from mathematics, statistics, and computer science to analyze instrumental data, clarifying the complex relationships between the composition or structure of substances and their performance [14]. Table 2 lists several commonly used chemometric methods in the food industry along with their applications.

Table 2. Chemometric methods applied in food analysis.

Method	Application
PCA	PCA, as a dimensionality reduction technique, effectively extracts the most significant features from the complex data obtained through sensory evaluation and instrumental analysis, utilizing them for sample classification and identification. Gao *et al.* employed PCA to establish distinctions in the concentrations of key chemical constituents among Pu-erh tea samples of varying grades and ages, thereby providing a scientific approach for the assessment of quality and authenticity of Pu-erh tea [13].
PLS	PLS regression is a valuable analytical tool in food analysis, facilitating the construction of predictive models for quality assessment. Borràs *et al.* integrated data from various instrumental techniques through data fusion and PLS regression analysis to forecast the sensory attributes of olive oil [15].
CA	In sensory analysis, CA helps identify natural groupings within data, often serving as a tool for exploring patterns and relationships in large datasets. Sun *et al.* integrated GC-MS data with sensory evaluation data and employed CA to identify the volatile compounds that significantly contribute to the sweetness perception of Baijiu [16].

Note: PCA, Principal Component Analysis; PLS, Partial Least Squares Regression; CA, Cluster Analysis.

In essence, chemometrics enhances sensory analysis by providing rigorous, quantitative methods to analyze and interpret the data, leading to deeper insights into the sensory properties of foods.

With the development of the food industry. A key research focus in sensory science is finding ways to overcome the limitations of human-based sensory evaluation, while also addressing the challenge that instrumental analysis techniques often struggle to provide comprehensive sensory experiences [17].

3. New technologies applied in sensory analysis

Intelligent sensory evaluation relies on smart sensory instruments such as electronic noses, electronic tongues, and electronic eyes. By simulating the functions of the olfactory, gustatory, and visual systems, these technologies capture characteristic signals through multiple sensors. Combined with machine learning and artificial intelligence, intelligent sensory evaluation provides multiple sensory characteristic data, effectively overcoming the limitations of traditional instrumental sensory technology [18].

Compared to traditional methods, electronic noses and tongues can rapidly analyze samples and simultaneously assess multiple parameters, significantly reducing analysis time. For instance, electronic noses can provide results within seconds when monitoring volatile organic compounds (VOCs), whereas gas chromatography-mass spectrometry (GC-MS) techniques may require more time and multiple operations to measure different indicators [19].

In industrial applications, real-time monitoring is often necessary, and electronic noses and tongues offer continuous detection data, which is crucial for applications requiring continuous surveillance of product quality or the detection of changes [19].

Although electronic noses and tongues offer numerous advantages, their drawbacks still limit their widespread use in industrial production. Compared to traditional instrumental analysis techniques, the cost is higher due to the frequent maintenance required to ensure accuracy. Additionally, sensor performance tends to degrade with use, and the replacement of sensors is also very expensive [20]. These factors increase the cost and complexity of use, making it difficult for these technologies to be widely applied by food industry. Furthermore, human olfactory and gustatory experiences are highly complex, capable of perceiving dozens of different stimuli simultaneously and providing a comprehensive evaluation. The number of sensors in electronic noses and tongues cannot match the level of human sensory organs, thus making it challenging to achieve a discrimination level for smell or taste that is close to human sensory perception [20].

4. Conclusion

While human-based sensory evaluation remains widely utilized and well-developed, it is inherently subjective variability, making the standardization and quantification of results challenging. To overcome these limitations, instrumental analysis methods have been introduced, allowing for the establishment of correlations between the chemical composition or physical properties of food and sensory evaluation outcomes. Despite the benefits, instrumental analysis generates vast and complex datasets, making the use of chemometric techniques for effective analysis necessary. As technology advances, innovative tools such as electronic noses and electronic tongues have been increasingly integrated into sensory analysis. Their ability to provide rapid, multi-indicator assessments is making them indispensable in modern industrial applications.

With the rapid development of computer technology, the integration of neural network algorithms, reinforcement learning, and machine learning into sensory analysis has become a research focus in recent years. As sensory analysis techniques advance and big data concepts are introduced, the complexity and dimensionality of sensory data have greatly increased. These algorithms facilitate feature selection, dimensionality reduction, and modeling, enabling the processing of large and complex datasets. Researchers can now digitize sensory information such as olfaction, taste, and vision, allowing for a more accurate interpretation of the relationship between food chemical composition and sensory experience.

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