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# From Traditional to Intelligent, A Review of Application and Progress of Sensory Analysis in Alcoholic Beverage Industry

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ABSTRACT

Sensory analysis is an interdisciplinary field that combines multiple disciplines to analyze food qualitatively and quantitatively. At present, this analysis method has been widely used in product development, quality control, marketing, flavor analysis, safety supervision and inspection of alcoholic beverages. Due to the changing needs of analysis, new and more optimized methods are still emerging. Thereinto, intelligent and biometric technologies with growing attention have also been applied to sensory analysis. This work summarized the sensory analysis methods from three aspects, including traditional artificial sensory analysis, intelligent sensory technology, and innovative technologies. Meanwhile, the application sensory analysis in alcoholic beverages and its industrial production was scientifically emphasized. Moreover, the future tendency of sensory analysis in the alcoholic beverage industry is also highlights.

## Abbreviations and nomenclature

| | |
|---|---|
| ISO | international organization for standardization |
| QDA | quantitative descriptive analysis |
| CATA | check-all-that-apply |
| RATA | rate-all-that-apply |
| TI | time-intensity |
| TDS | temporal dominance of sensations |
| ANOVA | analysis of variance |
| ODP | optimized descriptive profile |
| PM | projective mapping |
| MFA | multiple factor analysis |
| HCA | hierarchical cluster analysis |
| PMFA | procrustes multifactor analysis |
| GC-O | gas chromatography-olfactometry |
| PN | partial napping |
| GN | global napping |
| CP | conventional descriptive profiling |
| UFP | ultra-flash profiling |
| CA | correspondence analysis |
| PCA | principal component analysis |
| PP | pivot profile |
| JAR | just-about-right |
| TCATA | temporal check-all-that-apply |
| PSP | polarized sensory positioning |
| PPM | polarized projective mapping |
| BRT | boosted regression trees |
| E-nose | electronic nose |
| MOS | metal oxide semiconductor sensors |
| MOSFET | metal-oxide-semiconductor field-effect transistors |
| QMB | quartz microbalance sensors |
| LDA | linear discriminant analysis |
| SVM | support vector machines |
| KNN | k-nearest neighbor |
| RF | random forest |
| BPNN | back propagation neural network |
| RBFNN | radial basis function neural network |
| CNN | convolutional neural network |
| GC-MS | gas chromatography-mass spectrometry |
| MLP | multilayer perceptron |
| PLS | Partial Least Squares |
| E-tongue | Electronic Tongue |
| EEG | Electroencephalogram |
| fMRI | functional magnetic resonance imaging |
| fNIRS | functional near-infrared spectroscopy |

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## 1. Introduction

Sensory analysis is a scientific method of analyzing product characteristics by stimulating the assessor's senses. This analysis method is an interdisciplinary field that combines psychological, physiological, physical, chemical and statistical disciplines to measure and analyze food qualitatively and quantitatively (Lawless & Heymann, 2010).

Alcoholic beverages refer to beverages with ethanol for people to drink, which are divided into fermented alcoholic beverages, distilled spirit and integrated alcoholic beverages according to different production processes. Fermented alcoholic beverages (Y. Feng et al., 2022) are spirits produced by cellaring raw materials in airtight containers and fermenting them, such as beer, wine and so on. Distilled spirit (Zhao et al., 2018) are often obtained by using grain cereals as raw materials, fermenting them and then distilling the fermentation broth. Prepared spirits are different flavored spirits made from fermented and distilled spirits and blended with edible excipients or food additives.

In daily life, alcoholic beverages are often used as an important drink in social gatherings. As a key factor in consumer choice of alcoholic beverages, flavor often receives more attention. Therefore, it is necessary to describe and determine the aroma and taste of alcoholic beverages through sensory analysis. At present, sensory analysis has been widely used in product development, quality control (including aging and deterioration, production process monitoring), marketing, flavor analysis (Pauline et al., 2017; M. Ghasemi-Varnamkhasti et al., 2011; Dumitriu Gabur et al., 2019), quality and safety supervision and inspection (including adulteration) (W. Zhang et al., 2022) of alcoholic beverages. The types of alcohol involved are also very rich, including but not limited to wine, beer, brandy, whisky, vodka, Baijiu (Wiśniewska et al., 2017; Y. He et al., 2020), etc.

A literature survey was conducted through web of science on the application of different sensory analysis methods in different types of alcoholic beverages. Mapping of keyword data obtained from the Web of Science Core Collection database through visualization methods. According to the network visualization (Fig. 1), it is possible to analyze the correlations between keywords, the frequency of mentions, etc. And then the current research hotspots and the relationship between different methods and alcoholic beverages can be obtained. The network visualization (Fig. 1, a) shows that "QDA", "Napping", "CATA", "RATA ", "Projective mapping" are the same cluster, and "TI" and "TDS" are the same cluster. Electronic nose is often used for "differentiation", "geographic origin" and "identification" of samples. Electronic tongue is more commonly used for "prediction" and "classification" of samples, while "sensor" and "neural-networks" are also often mentioned together. EEG and facial expression analysis are often used for "emotion" and "behavior" studies. The keyword burst analysis was performed by restricting the years from 2015 to 2023. The keyword bursts (Fig. 1, b) show that the burst year of "CATA" and "machine learning" in the research of analytical methods are closer to now, and the burst end time of "machine learning" is 2023, indicating that it is a hot spot of current research. The keyword bursts (Fig. 1, c) shows that the burst year of "origin", "willingness to buy", and "consumer perception" in the study of sensory analysis research purposes are closer to now. The intensity of the prominence of "willingness to buy" is also relatively strong, which also shows that sensory analysis has been more used for consumer research in recent years.

With the development of sensory analysis, it was gradually realized that expert assessors with experience were a minority and that experts in different aspects could have emotional tendencies and subjective biases. Therefore, intelligent sensory techniques that mimic human sensory organs becoming more prevalent. Currently, sensory analysis is also heavily used to consumer test, and the application of biometric techniques to obtain consumers' unconscious responses to food stimuli is an area that is gaining attention. Fig. 2 shows the basic principles and similarities and differences of three types of sensory analysis approaches: artificial sensory analysis, intelligent sensory technology, and innovative techniques in sensory analysis.

At present, sensory analysis also has some limitations. Since the development of sensory analysis, a variety of methods have been accumulated. Different foods have different characteristics. It is also the

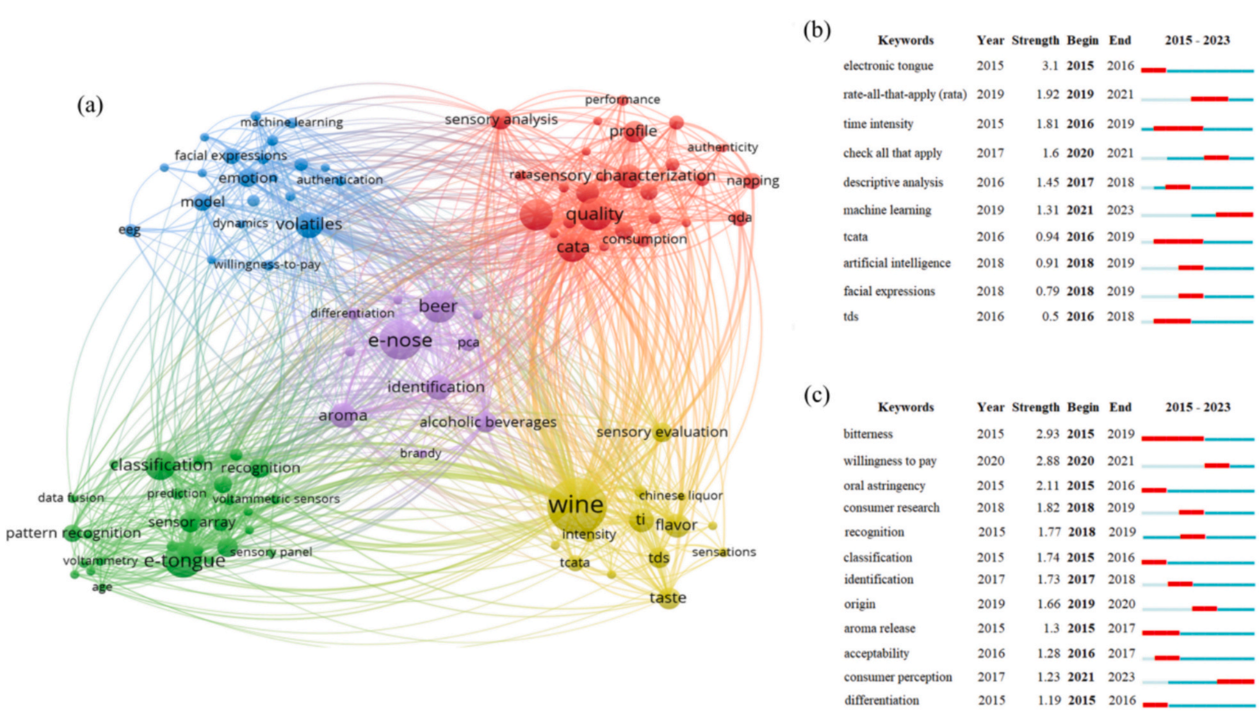



**Fig. 1.** . Recent trends and research hotspot of Sensory Analysis in Alcoholic Beverage Industry (a: Network visualization of keyword for sensory analysis in alcoholic beverage applications. Different colors represent different clusters, and the circle and its name form an element. The size of the element depends on the frequency of keyword mentions, the strength of the connecting lines, etc.; b: The keyword with the strongest citation bursts of sensory analysis method in alcoholic beverage industry. c: The keyword with the strongest citation bursts of sensory analysis purpose in alcoholic beverage industry.)

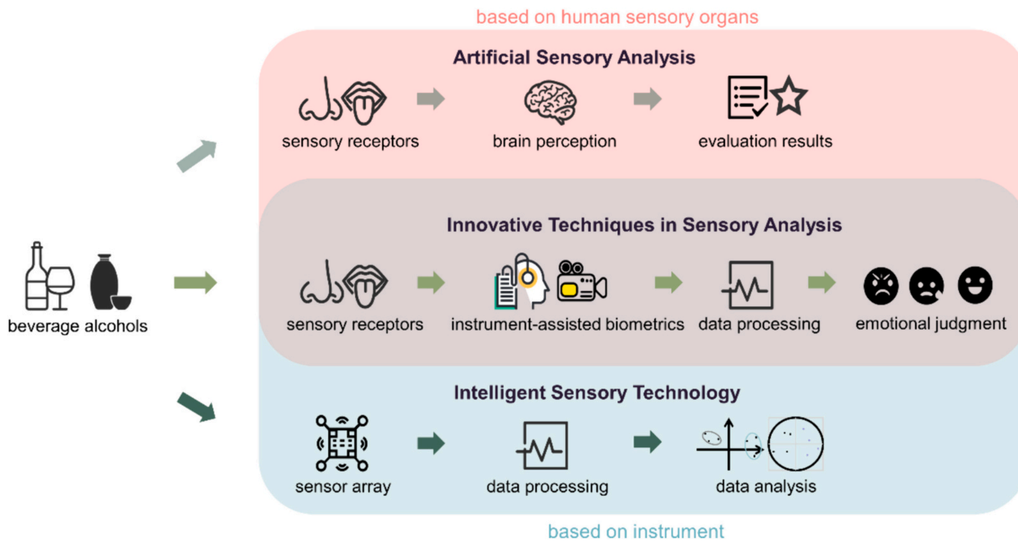



**Fig. 2.** . The basic principles of the three types of sensory analysis methods

direction of the development of sensory analysis methods to adjust and improve the existing analytical methods or a combination of methods according to the known methods combined with food characteristics and analysis purposes. However, there is a lack of systematic introduction to facilitate the selection of methods according to different purposes. In addition, there are differences in the application of sensory analysis in laboratories and factories. Sensory analysis for laboratory use often ignores time and labor, but in actual production labor and time costs are important factors that cannot be ignored. Therefore, sensory analysis methods are also evolving towards being faster, easier and less subjectively biased.

This work presents a summary of sensory analysis methods often applied in the field of alcoholic beverage, and list application examples to provide a reference for the selection of sensory analysis methods and the optimization and adjustment of sensory analysis methods for the alcoholic beverages industry in the future. Table 1 lists the applications of sensory analysis in alcoholic beverages as mentioned in this work. Table 2 lists the advantages and disadvantages of sensory analysis methods.

## 2. Artificial Sensory Analysis

Traditional sensory analysis is a measurement that is conducted with the human sensory system as the main body. The applications of traditional sensory analysis are broadly divided into four categories: difference identification, difference scale and category, descriptive analysis, and consumer test (Damir D. Torrico et al., 2023). Difference identification is required to determine whether there is a difference between two and more samples. Difference scale and category is required to evaluate the size of difference, the order of difference, or to categorize samples for more than two samples. Descriptive analysis is required to analyze qualitatively and quantitatively the intensity of some or some properties of the sample. Consumer tests is more focused on understanding consumers' hedonic and emotional reactions to products.

Triangle test is the more classical method of difference identification. Triangle test (ISO-6658:2017, 2017) is an inspection method that simultaneously provides three coded samples, two of which are identical, and requires the assessor to pick out the different samples among them. This method is commonly used in quality control to evaluate subtle differences between samples. In addition to this, in the wine industry, the ability to pass the triangle test is often used as a criterion for selecting assessors.

Ranking test is the classical method of differential scaling and classification tests. Ranking test is a method of comparing several samples at the same time and ranking them according to the specified characteristics by strength or preference. The method requires only the order of the samples to be discharged and does not require the evaluation of the magnitude of the differences between the samples.

Hedonic scale is the classic emotion testing method. Hedonic scale is commonly used in measuring product and preference, with the 9-point hedonic scale being the most effective sensory method. The method usually gives the assessor a scale of nine expressions, such as "dislike extremely, dislike very much, dislike generally, dislike slightly, dislike nor dislike, like slightly, like generally, like very much, like extremely", corresponding to the numbers 1-9. Allow the assessor to select the option that best represents the attitude towards the sample under test from the scale. This method is very simple and easy to use, and is now commonly used in consumer tests. Today, as the field of sensory analysis continues to evolve and explore whether biometrics can be used as a method to determine consumers' potential affective tendencies, the 9-point hedonic scale remains the best complementary method.

With the change of evaluation requirements, sensory analysis methods are also constantly developing. Current analytical methods in common use are also not limited to the overall evaluation of the sample, but even give temporal attributes to sensory analysis. Therefore, this work will present a summary of the artificial sensory analysis from both static and dynamic aspects.

### 2.1. Static sensory analysis

Static sensory analysis is the traditional classical method. Static methods relatively provide a single assessment of sensory characteristics, and the results are a comprehensive evaluation of the overall perception of the individual time or the assessment process (Alcaire et al., 2017). In the current sensory analysis system, static sensory analysis is still the main body used.

No matter which method is used, sample preparation, assessor determination, test room setting and descriptor lexicon establishment are all required before sensory analysis. After completing these tasks, the specific analysis process will be carried out. In artificial sensory analysis, the choice of assessors largely determines the results of the analysis. Therefore, different assessors need to be selected according to the different analysis needs. The specific method of screening and training of assessors can be referred to ISO 8586: 2023 (ISO-8586:2023, 2023). The setting of the test room is equally important. An appropriate testing environment can minimize the physical and psychological disturbance

**Table 1**
. Application of sensory analysis in alcoholic beverages

| Methods | Alcoholic Beverages | Assessor | Utilization purposes | Sensory attributes | Reference |
|---|---|---|---|---|---|
| QDA | Wine | well-trained assessors | Describe the aromatic characteristics of the wine. | Aroma: red fruit, leather, tobacco, prune, liquorice, fresh, clove, coffee and caramel. | (Sanchez-Palomo et al., 2017) |
| QDA | Rum | well-trained assessors | Quantify sensory differences between samples. | Aroma: brown sugar, caramel, maple, vanilla, coconut, citrus, phenolic, alcohol, smoky, roasted and chocolate;<br>Mouthfeel: slick and warming;<br>Taste: bitter;<br>Aftertaste: brown spice and caramel;<br>Aroma by Mouth: caramel, maple, vanilla and coconut. | (Ickes & Cadwallader, 2017) |
| QDA, Napping | Wine | test-passed assessors | Distinguish samples from different regions and describe aroma characteristics. | Aroma: red fruits, smoky, prune, baking, green pepper, black currant, sweet spices, hawthorn, stone fruits and floral. | (Tang et al., 2020) |
| Napping-UFP | Brandy | well-trained assessors | Verify whether two Napping techniques (GN、PN) are still accurate in high alcoholic beverage. | Color: dark gold, copper-tinged, yellow, dark yellow and orange;<br>Aroma: coffee, apricots, citrus, fresh apple, chocolate, cigar box, earthy, herbaceous notes, wood-matured, nutty, liquorice, tobacco, raisin, smoky, spicy notes, almonds, grassy and peach notes;<br>Mouthfeel: oily, watery. | (Louw et al., 2013) |
| Napping | Brandy | well-trained assessors | Optimization of the PN method. | - | (Louw et al., 2015) |
| Napping-UFP | Wine | well-trained assessors | Compare the sensory differences of the samples and describe their aroma characteristics. | Color: purplish;<br>Aroma: floral, alcoholic, yeast, dairy, raisin fruit, red fruit, balsamic, fresh, ripe fruit, cherry;<br>Taste: sweet, bitter, spice;<br>Mouthfeel: astringent. | (Perez-Navarro et al., 2019) |
| Napping-UFP | Wine | well-trained assessors | Verify that the method is able to identify differences between samples with similar flavors. | Aroma: earthy, grapefruit, cherry, green, jam, vegetal, floral, spice, herbaceous, medicinal, black fruit, strawberry;<br>Taste: bitter, astringent, acidity, tannic;<br>Mouthfeel: delicate, hot. | (Kemp et al., 2018) |
| Napping-UFP | Wine | expert assessors | Sensory analysis of wines with different amounts of $CO_2$ substitution. | Taste: fresh, creamy, bitter, acid, complex;<br>Mouthfeel: persistent;<br>Aroma by Mouth: fruity, apple, banana, peach, melon, herbaceous, pear, floral. | (Izquierdo-Cañas et al., 2021) |
| CATA | Wine | consumers | Explore the effect of adding oak chips from different regions as an alternative to wooden barrels as an aging tool during fermentation. | Color: light red color, deep red color;<br>Aroma: bouquet, herbaceous, red fruit, vanilla, woody, spicy, vegetal, aromatic, grape, persistence of flavor;<br>Taste: sourness, sweetness, bitterness, alcoholic;<br>Mouthfeel: dryness; watery, body, equilibrate. | (Alencar et al., 2019) |
| CATA, RATA | Wine | well-trained assessors, consumer | Assessing the astringency. | Mouthfeel: silk, velvet, dry, corduroy, adhesive, aggressive, hard, soft, mouthcoat, rich, full-body, green, grainy, satin, pucker, persistent. | (Rinaldi et al., 2021) |
| CATA, QDA | Wine | well-trained assessors, semi-trained assessors, consumer | Compared the results of sensory analysis by trained assessors、semi-trained assessors and consumers. | Appearance: purplish, reddish, clear;<br>Aroma: fresh fruit, fruit jam, dried fruit, spice, vegetal, flower, smoked, vinegary, alcoholic,<br>Taste: sweetish, sour, bitter;<br>Mouthfeel: astringent, full-bodied, pungent;<br>Aroma by Mouth: alcoholic, fresh fruit, Fruit jam, dried fruit, woody. | (Veríssimo et al., 2020) |
| RATA | Wine | semi-trained assessors | 46 samples were evaluated and analyzed for commonalities and differences. | Aroma: citrus, tropical fruits, red fruits, wild berries, fruit tree, nuts, baked fruit, white floral, red floral, vegetative, balsamic, spices, earthy, roasted, woody, caramelised, yeast, ethereal, animal;<br>Taste: sweet, sour, bitter, salty;<br>Mouthfeel: astringency, alcohol, body. | (Rabitti et al., 2022) |
| RATA, hedonic rating | Wine | consumers | Explore whether origin affects consumer purchase intentions and sensory perceptions. | Aroma/ Aroma by Mouth: barnyard, coconut, confectionery, cooked vegetables, dark fruits, dried fruits, earthy, eucalyptus, floral, grassy, green, herbaceous, jammy, liquorice, minty, oaky, pepper, oaky, pepper, red fruits, savoury, spices, tobacco, vanilla/chocolate, violets;<br>Taste: acidity, bitterness, sweetness;<br>Mouthfeel: alcohol, astringency, body. | (Souza Gonzaga et al., 2022) |
| PSP, PM | Rice wine | consumers | Investigate the product categorization and characterization of rice wine among beer and wine samples. | Taste: bitter, sour, sweet;<br>Mouthfeel: astringent, dry, creamy;<br>Aroma by Mouth: dark, fruity, light, pleasant, strong and unpleasant. | (Wong et al., 2024) |

(continued on next page)

**Table 1** (*continued*)

| Methods | Alcoholic Beverages | Assessor | Utilization purposes | Sensory attributes | Reference |
|---|---|---|---|---|---|
| PPM | Wine | expert wine professionals, consumers | Investigate the fruitiness aroma perception of white wines. | Aroma: tropical fruit, stone fruit, citrus, pome, floral, confectionary, vegetal, oaky, volatile, Spoilage, melon, berry, faint. | (Iobbi & Tomasino, 2021) |
| PPM | Wine | well-trained assessors | To test the applicability of PPM to dry South African Chenin Blanc wines. | Aroma: grapefruit, green, apple, lemon, mango, passion fruit, pineapple, guava, spice, coconut, nutty, toasted bread, buttery, planky, smokey, dried fruit, toasted, vanilla, caramel, oaky/ wooded. | (Wilson et al., 2018) |
| TI, CATA | Wine | well-trained assessors | Assessment of the astringency intensity of wines and analysis of the relationship between astringency and phenolic composition. | Mouthfeel: astringency (dry, rough, aggressive, sand paper, puckery, harsh, abrasive, hard, coarse grain, irritant, complex, silky, fine emery, suede, mouthcoating, and velvety). | (Vidal, Ares, et al., 2018) |
| TI | Wine | test-passed assessors | Explore the postnasal aroma intensity of two specific aroma attributes. | Aroma by Mouth: black pepper and smoked. | (Criado et al., 2021) |
| TI, TDS | Baijiu | trained assessors | Evaluation of the temporal characteristics of the pungency intensity of Baijiu with different aging times, and evaluation of the subqualities of pungency. | Mouthfeel: pungency (Burning, Tingling, Numbing, Prickle, Salivating and Drying). | (He et al., 2021) |
| TDS, hedonic rating | Beer | consumers | Understanding consumers' sensory analysis and preference for two types of beer. | Taste/ Aroma by Mouth: sweet, malt, red fruits, bitter, hops, sour and yeast. | (Machado et al., 2023) |
| E-nose | Kiwifruit wine | instrument | Aroma assessment of 14 commercially available samples. | Differential analysis only, no specific sensory attributes. | (Lan et al., 2022) |
| E-nose | Wine | instrument | Monitoring thresholds of acetic acid in samples. | Aroma: acidity. | (Rodriguez Gamboa et al., 2019) |
| E-nose | Wine, Baijiu | instrument | Build recognition models and use electronic noses combined with machine learning techniques to identify samples. | Differential analysis only, no specific sensory attributes. | (Yang et al., 2020) |
| E-tongue | Wine | instrument | Explore the effects of different oak barrels on ageing and predicting the maturity of wines. | Differential analysis only, no specific sensory attributes. | (Ceto et al., 2017) |
| E-tongue | Wine | instrument | Measure the components that cause defects in the wine and distinguish the original wine sample from the adulterated wine sample. | Adulteration analysis only, no specific sensory attributes. | (Lvova et al., 2018) |
| E-nose, E-tongue | Rice wine | instrument | Identify wine samples of different vintages. | Age identification only, no specific sensory attributes. | (Zhang et al., 2020) |
| E-tongue, Flash Profiling | Wine | trained assessors, instrument | Two methods were used to analyze the sensory changes in the samples caused by spoilage due to different microorganisms. | Aroma: dairy, fermentation, earthy, chemical/ solvent, rotten and putrid, animal, savory, and veggie. | (Paup et al., 2021) |
| EEG, hedonic rating | Beer | beer-expert assessors, general assessors, consumers | Compare the results of different assessors using these two methods. | Hedonic evaluation only, no specific sensory attributes. | (Hinojosa-Aguayo et al., 2022) |
| EEG, Facial Expression Analysis, hedonic rating | Beer | consumers | Assessing consumers' preferences. | Appearance: foam stability, foam height, color; Aroma: overall; Taste: bitter; Mouthfeel: carbonation; Aroma by Mouth: overall. | (Gonzalez Viejo et al., 2019) |
| Facial Expression Analysis | Beer | consumers | Assessing consumers' preferences. | Hedonic evaluation only, no specific sensory attributes. | (Wakihira et al., 2022) |

to people and thus reduce the bias of the results. The design of test room can be referred to ISO 8589: 2007 (ISO-8589:2007, 2007) and amendment 1. The establishment of descriptor lexicon is not entirely necessary. In the free description method, it is not necessary to organize the vocabulary in advance, and it is enough to let the assessors write down the descriptions freely according to their sensory perceptions. For other methods, details of the descriptor lexicon establishment can be found in ISO 11035: 1994 (ISO-11035:1994, 1994). In addition to the above preparations, it is particularly important to note that sensory analysis with human participants requires completion of an ethics protocol and signing of an informed consent form prior to testing. In the test of alcoholic beverages, it is particularly necessary to pay attention to health issues, including whether there are allergies, symptoms of alcohol intolerance, and the presence of respiratory and cardiovascular diseases that preclude alcohol consumption.

The number of static sensory analysis methods is large, and four commonly used methods have been selected for introduction.

#### 2.1.1. *Quantitative Descriptive Analysis (QDA)*

QDA is one of the most classic methods of descriptive analysis. It is still heavily used in the alcoholic beverage industry. QDA requires the assessor to describe as completely as possible the sensory characteristics of the perceived sample and to evaluate the strength of each indicator.

QDA in sensory analysis applications, specific operations (Fig. 3) include: ①Conduct screening and training of assessors. Professionals need to be selected as assessors in this method, so before the formal evaluation, 10-12 assessors need to be selected and trained according to the purpose of the test, so that they can reach a consensus on the identification and strength quantification of sensory attributes. ②Initial evaluation of the subject samples was performed by well-trained assessors from sensory panel and initial descriptors were generated after brainstorming. ③The initial screening of the descriptor lexicon of brainstorms followed by intensity evaluation. ④The descriptors were sorted and censored according to the descriptor mention ratio and intensity ratio to form the descriptor lexicon for this sample. And gives a definition and reference for each descriptor in the descriptor lexicon. ⑤Intensity evaluation was done for the descriptors in the finalized

**Table 2**
Advantages and disadvantages of sensory analysis methods

| Methods | | Advantages | Disadvantages | Application |
|---|---|---|---|---|
| QDA | QDA | Effectively distinguish and classify and quantify sensory differences; The method is mature. | Need trained assessors; Pre-training takes a long time. | Prefer QDA for sensory analysis when sample volume is large. |
| | ODP | Optimized QDA; Reduce the time spent on pre-training. | Sensory fatigue; Cumbersome data processing | |
| Napping | | Quickly obtain the differences between products. | Difficulty in evaluating samples when they are similar, while accuracy decreases; Difficulty in obtaining sensory attribute information. | PN obtained relatively better results when specific sensory attributes are evaluated or when the sample size was large. |
| CATA | | Rapid sensory analysis method; Simple, convenient and easy to operate. | Evaluation of similar samples is more difficult. | CATA is the best choice when differences between samples depend on sensory attributes; RATA is a better choice when sensory characteristics are similar but the intensity is different. |
| RATA | | Rapid sensory analysis method; Simple, convenient and easy to operate. | Need to focus on filtering descriptors to avoid long questionnaires when sample size is large. | |
| PSP | | | Dependent on the choice of reference point. | All apply to comparisons between products; PSP is more suitable for product evaluation with large sample size; PPM is two-dimensional in nature; PP is more suitable for evaluation of similar products. |
| PPM | | Efficiently; Can effectively distinguish samples and obtain sensory attributes. | Dependent on the choice of reference point. | |
| PP | | | The large number of sensory attributes leads to cumbersome data processing. | |
| TI | | Get the change of specific attributes. | Only a small number of samples or a small number of sensory attributes can be evaluated; "halo-dumping" effect. | TI focuses more on the evolution of the strength of individual attributes; TDS is used to deal with the interaction between attributes and the overall evaluation. |
| TDS | | Short experimental time; Avoid "halo-dumping" effect. | Inability to access the complete pattern of intensity changes for individual attributes. | |
| E-nose | | Rapid evaluation; Avoid subjectivity; Avoid the paralyzing effects of alcohol. | Requires some upfront database building; Sensor-dependent. | It has good applications in terms of origin, adulteration, vintage, category, quality and safety. |
| E-tongue | | | | |
| EEG | | More objective test results. | EEG signals are sensitive and testing is equipment and environment dependent. | Suitable for use in consumer testing. |
| Facial Expression Analysis | | | Limited by shooting environment, the resolution and sensitivity of the camera; Cumbersome data processing | |

lexicon of descriptor words. ⑥The evaluation results of the sensory panel (after removing the most deviated data) were averaged and analyzed using Analysis of Variance (ANOVA) and multivariate statistical techniques. QDA data are not generated through consistency discussions and do not look at the evaluation results of a particular individual, but rather through statistical analysis of sensory panel's evaluation results, which can more objectively and accurately reflect the characteristics of the sample under test.

Wine was characterized by instrumentation and QDA to characterize the aromas. 10 well-trained assessors were selected to perform quantitative descriptive sensory analysis of wines from a specific region for four consecutive years (Sanchez-Palomo et al., 2017). The aroma characteristics of the wine in the region were obtained, from the average aroma intensity scores and standard deviation analysis of the test results. Rum was used to quantify sensory differences between samples by QDA and Spectrum methods (Ickes & Cadwallader, 2017). Based on the analysis of the results of the preliminary evaluation, the sensory attribute words were identified and the spider plots were drawn according to the intensity of the attributes. From the data analysis results, the distinction between different samples in terms of specific attributes can be clearly obtained. Now QDA is more commonly used as part of flavoromics to evaluate the flavor attributes of alcoholic beverages rather than on its own (Perez-Jimenez et al., 2021).

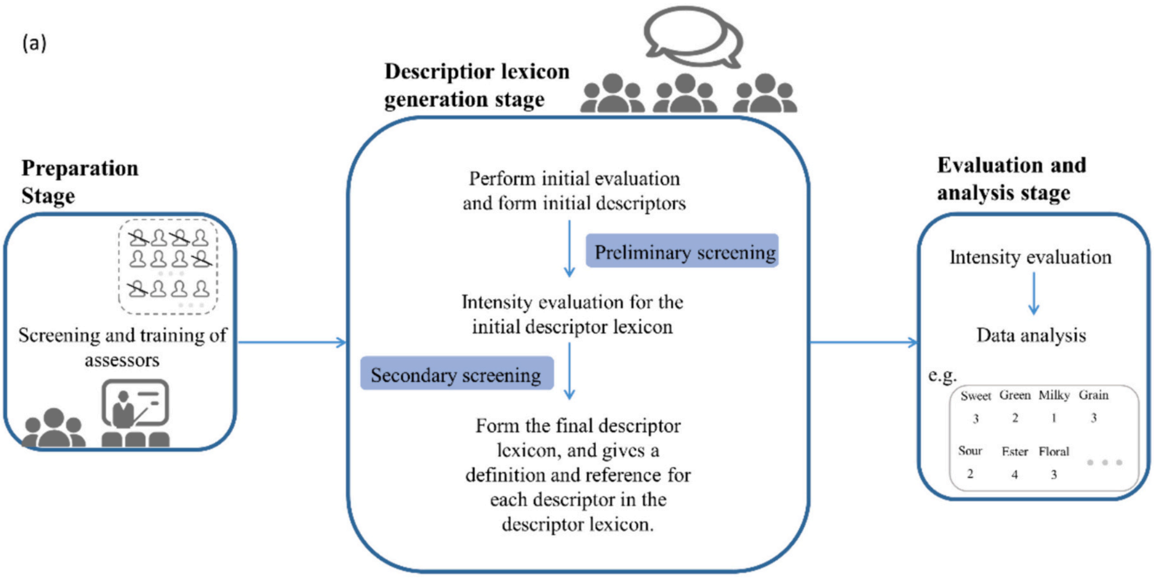
QDA is a method that can effectively distinguish differences in aroma intensity and classify and quantify sensory attributes, and is therefore used extensively in the field of food sensory analysis. However, QDA requires the selection of professionals as assessors and takes a long time to train. Therefore, a new descriptive analysis method, called optimized descriptive profile (ODP), was proposed in 2012 by Silva et al. (Minim et al., 2012). ODP is actually the optimized QDA method, which reduces the training time for assessors. In this method, a reference sample and a scale are prepared for assessors. The assessor only needs to compare the sample under test with the reference sample and mark the sensory intensity on the scale. However, ODP still has some limitations. First of all the method can fatigue the senses of the assessor in cases where there are particularly many sensory attributes. Secondly the method uses a scale instead of a scoring, which adds a burden to the subsequent data processing. In summary ODP has the potential to reduce the time and cost of finding professionals and training up front in descriptive analysis.

### 2.1.2. *Napping*

In the alcoholic beverage industry, the characterization of the tested samples usually relies on the evaluation of professionals. However, the small number of professional sommeliers in the wine industry makes this difficult to achieve, as using professionals for evaluation requires a lot of time for pre-training. Projective mapping (PM) was introduced to the field of food sensory analysis by Risivik et al. (Risvik et al., 1994) as a method to obtain differences between products quickly. The advantage of this method is that it does not require training of the assessor and can meet the needs of analyzing samples. Napping is a method derived from PM and originally appeared in the wine industry (Pagès, 2003). The difference between PM and Napping is always blurred in practical applications. In fact, Napping is only available for rectangular frames (60 × 40 cm) and the data cannot be deflated until the data results are analyzed using methods such as multiple factor analysis (MFA) (Dehlholm et al., 2012).

The principles of Napping and PM are basically similar, with the following specific operations: ①Give the assessor a 60 x 40 cm (approximately A2 size) sheet of paper and all samples. ②Assessors place samples on the paper according to their perceptions. The distance between the samples is used to indicate their variability. ③The initial data collected are from measurements of the distance placed between samples. The measured data are usually analyzed using MFA, plot with the result of hierarchical cluster analysis (HCA), and procrustes multifactor analysis (PMFA) (Morand & Pagès, 2006).

Cabernet Sauvignon wines from four regions in China were




(b)

| Samples | Sensory characteristics | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Appearance | | Aroma | | | | | Taste | | | Mouthfeel | | | | | | Flavour style |
| | Colorless | Transparency | Jiao-aroma | Grain aroma | Floral aroma | Chen-aroma | … | Sweet taste | Sour taste | … | Softness | Fullness | Harmony | Purity | Persistence | … | Typical style/special style |
| Sample 1 | 7 | 7 | 8 | 5 | 6 | 4 | | 6 | 3 | | 8 | 4 | 6 | 4 | 3 | | 8 |
| Sample 2 | 8 | 7 | 7 | 6 | 4 | 1 | | 5 | 5 | | 7 | 5 | 7 | 3 | 5 | | 6 |
| …… | | | | | | | | | | | | | | | | | |

**Fig. 3.** . a: Operation process of QDA (The descriptor lexicon generation stage process is also applicable to other methods that require pre-screening of descriptors.) b: The QDA score table for Baijiu as an example.

characterized by QDA and Napping combined with GC-O (Tang et al., 2020). The results showed that the flavor characteristics of Cabernet Sauvignon wine from the Loess Plateau region were different from those of other regions. The typical characteristics of wines from the Loess Plateau region were analyzed by Napping and QDA, and their conclusions were certified by GC-O. Napping is divided into global Napping (GN) and partial Napping (PN). The PN and GN methods were used to compare six brandy samples to verify that both methods were still accurate in high alcohol beverages (Louw et al., 2013). The test was referenced to the results of the conventional descriptive profiling (CP) method and found to be equally reliable and reproducible for PN and GN. However, when the number of samples is too large, PN will relatively obtain better results. This may be because the GN needs to evaluate the overall sensory of the sample, while the PN can choose to focus on different sensory characteristics one at a time and evaluate them separately. The following year, the team (Louw et al., 2015) tried three options to optimize the GN method.

In order to reduce time and labor costs, sensory analysis is also gradually tending to use simpler, faster and more accurate analysis methods. Napping offers such advantages. Napping can also be used for consumer tests to understand consumer preferences and acceptance of products. However, napping still has shortcomings. On the one hand, the evaluation process becomes more difficult when the samples are too similar to each other, and it also leads to a decrease in accuracy. On the other hand, napping only evaluates the similarities and differences between samples, and does not evaluate the sensory attributes of the samples, obtaining less information about the sensory attributes. Therefore, it has been proposed that at the end of the napping procedure, the assessor is asked to write down 1-3 distinguishing and typical descriptors (which can be words describing the degree) next to each sample, after which the vocabulary is statistically categorized. Such an approach is called Ultra-Flash Profiling (UFP). (Oliver et al., 2018) compared the results of a well-trained assessors from sensory panel using QDA with the results of untrained consumers applying napping combined with UFP. It is found that the combination of napping and UFP can replace QDA under the condition of controlling time cost.

The sensory characteristics of Moribel, Tinto Fragoso and Tempranillo were evaluated by a panel of professional assessors use Napping combined with UFP methods over a two-year period (Perez-Navarro et al., 2019). The first year's results showed that both Moribel and Tempranillo had cherry fruit aromas, while Tinto Fragoso had a more intense and persistent aroma. In the second year, Moribel's ripe fruit and forest berry notes were more prominent, while Tempranillo's characteristic aroma was red fruit. The PN combined with UFP method was used for sensory analysis of wines that had undergone multiple treatments and it was found that this method could identify differences between samples with similar flavors (Kemp et al., 2018). $SO_2$ used as a preservative in wines and since it impairs the sensory quality (Oliveira et al., 2011), $CO_2$ was used instead of $SO_2$. Napping combined with UFP was used for sensory analysis of wines with different amounts of $CO_2$ substitution (Izquierdo-Cañas et al., 2021). The GC results showed that the acetaldehyde content decreased and the organic acid content increased as the amount of carbon dioxide substitution increased. This has a positive impact on the aroma of the wine. The sensory analysis also revealed that the wines with 100% $CO_2$ substitution were selected as the most aromatic wines and that the stability of the wines was not affected.

#### 2.1.3. Check-all-that-apply (CATA)

CATA is a rapid sensory analysis method that provides the assessor with a descriptor questionnaire and requires the selection of all appropriate sample terms.

CATA in sensory analysis applications is relatively simple, specific operations include: ①Descriptor questionnaire generation by trained sensory panelists. Professional panelists are able to describe the samples more comprehensively (Dooley & Meullenet, 2010), but care needs to be taken to retain the professional descriptions and definitions while keeping them as simple as possible to make them more understandable to the average consumer. On the other hand, it is also important to note that the length of the questionnaire (Sara R. Jaeger et al., 2015) and the ordering of the descriptors need to be considered when generating the questionnaire. ②Depending on the purpose of the sample evaluation, trained assessors or consumers can be selected to conduct the questionnaire evaluation. ③After the end of the questionnaire, the questionnaire data were sorted according to the frequency of description word selection. Cochran's Q test can be used to confirm significant differences between each sample. Correspondence analysis (CA) and principal component analysis (PCA) are commonly used to analyze the results of descriptors.

CATA was used to investigate the effect of adding oak chips from different regions as an alternative to wooden barrels as an aging tool during fermentation (Alencar et al., 2019). The results showed that oak chips did affect the sensory characteristics of the wines. American oak chips provided a stronger aroma of wood and coffee, while French oak chips increased sweetness. At the same time, considering consumer acceptance, it was found that the differences due to oak chips did not affect consumer acceptance of the wines. CATA has also been used to assess the astringency of wines through consumers and trained assessors (Rinaldi et al., 2021). Twenty-five astringency subqualities sensory descriptors were selected. By comparing the evaluation results, it was found that there were some differences in the frequency and preference of ticking descriptors between consumers and evaluators. This should be due to the fact that consumers rely solely on the definitions given to make judgments, and there is some difference in perception between trained evaluators. The results of CATA analysis of wine by trained assessors and consumers were compared and found that there were some differences in their results (Veríssimo et al., 2020). Therefore, in more complex sensory analysis, trained assessors are preferred to conduct them.

Based on CATA, a method called pick-K is proposed. Compared with CATA, pick-K does not need to describe the complete attributes of the sample, but only needs to select the dominant K attribute in the product (Franco-Luesma et al., 2016). As a simple, convenient and easy-to-use sensory analysis method, CATA has been derived from many methods combined with CATA in order to achieve more evaluation requirements in practical applications. For example, Pivot-CATA (S. Wang et al., 2023) combining pivot profile (PP) with CATA, CATA-JAR (Lee et al., 2021) combining just-about-right (JAR) with CATA, temporal check-all-that-apply (TCATA) (Castura et al., 2016) combining dynamic sensory analysis. So far, sensory analysis in the form of questionnaires is no longer limited to evaluation using questionnaires consisting of all descriptors words. Emoji substitution words were introduced in some experiments to measure consumer emotional responses (Sara R. Jaeger et al., 2018).

#### 2.1.4. Rate-All-That-Apply (RATA)

The convenience of CATA also makes the method somewhat problematic. CATA does not directly evaluate the strength of sensory attributes in the evaluation process, so there are limitations in distinguishing subtle differences in a sensory attribute. Therefore, RATA is proposed on the basis of CATA (Reinbach et al., 2014). RATA requires that the intensity of the ticked sensory attributes be evaluated after the descriptor questionnaire has been selected (Ares et al., 2014). A score of 5 or 7 was selected for evaluation on the general intensity scale.

The RATA method was used for the evaluation of wines by semi-trained assessors (Rabitti et al., 2022). The results showed that RATA was able to identify different types of wines and select their sensory attributes. RATA combined with hedonic rating method was used to analysis Cabernet Sauvignon wines from four producing areas (Souza Gonzaga et al., 2022). The study was conducted primarily on consumers. According to the results of the sensory analysis, some wines have distinct regional characteristics, so consumers are also able to distinguish between wines from different regions based on sensory characteristics.

RATA does not have major defects in the current application of sensory analysis. However, when RATA is used to evaluate a large sample, it is necessary to focus on screening the descriptors of the questionnaire. Try to avoid long lists, so that the descriptors in the questionnaire are all as relevant as possible. In order to avoid sensory fatigue of the assessor during the sensory analysis process and reduce the accuracy (Vaikma et al., 2021). Like CATA, a variant method called reta-K is also proposed based on RATA. Like pick-K, this method focuses only on the dominant K attributes, so a small number of attributes need to be rated (Saenz-Navajas et al., 2020).

By comparing the two methods, CATA questions should be the best choice when the difference between samples depends on the presence or absence of sensory attributes on the questionnaire. The use of RATA questions is more recommended when samples with similar sensory characteristics but different intensities (Vidal, Ares, Hedderley, Meyners, & Jaeger, 2018).

#### 2.1.5. Other methods

With the development of sensory analysis methods, hundreds of self-reported evaluation methods have been utilized in food science (Visalli et al., 2023). The above mentioned methods are the more mature and frequently used static sensory analysis methods in the alcoholic beverage industry. Although QDA is the most commonly used tool, rapid sensory analysis has also been gradually set up to comply with the growing needs of the food industry. The CATA and RATA mentioned in the appeal are verbal-based analysis methods. In addition, reference-based rapid sensory analysis methods, such as Polarized Sensory Positioning (PSP), Polarized Projective Mapping (PPM) and Pivot Profile (PP), are currently receiving more attention.

The PSP method needs to set the pole before experiment. In the subsequent process, the sample is compared with the pole in sequence, and the similarities and differences between the samples and the poles are quantified by the scale. At the same time, comparative or subjective terms can be recorded for each sample, and sensory attributes can also be collected (Heo et al., 2023). PM and PSP were applied to analysis rice wine and the comparison reveals that since PSP is more instructive than PM. The PSP does not have to classify products but directly compares with poles. Therefore, PSP is more suitable for product analysis with larger sample size than PM (Wong et al., 2024).

PPM combines the positive aspects of Napping and PSP. The actual operation of PPM is roughly similar to Napping, which is positioned on a piece of paper. The samples close to each other are similar, and the samples far away are different. However, Napping requires a comparison between each sample, which limits the number of samples that can be characterized. PPM is to place three reference samples or extreme points on paper against which the sample being evaluated needs to be compared with these three samples. In addition, PPM collects sensory descriptors of the samples, which are no longer limited to sample comparison, but rather to obtaining more stable free description results (Ares et al., 2013). In particular, a sample other than wine may be selected as a reference sample when analyzing the wine. Melon, citrus, tropical fruit, pear, and stone fruit were set as ‘fixed poles’ to evaluate the fruity aromas of white wines (Iobbi & Tomasino, 2021). In the use of PPM, the choice of reference points is crucial, and the choice of reference samples or poles has an impact on the results of sensory characterization to certain extent (de Saldamando et al., 2015). In some practical applications, PM experiments were used as pre-experiments and the three poles were determined based on the experimental results (Wilson et al., 2018). The pole selected by PM was placed in advance and then the PPM program is performed.

PP is a free description method based on reference samples. When performing PP, the samples to be analyzed is paired with the reference sample. The stronger and weaker sensory attributes of the samples to be evaluated than the reference samples were recorded respectively (Thuillier et al., 2015). This method is easy to implement and has a specific description of the product. It has potential as a sensory perception technique used by consumers (Esmerino et al., 2017). Beer was used as an example to investigated the selection of pivots in PP and the influence of product similarity on the method (Lelièvre-Desmas et al., 2017). It was found that the PP method differentiated the samples better when the similarity between the samples was higher. The choice of pivot was found to give very similar results even when different pivots were chosen. Therefore, in this method, the selection of pivot is relatively not very harsh.

At present, the application of these three methods in alcoholic beverage industry is still less. However, these methods can quickly distinguish products and provide descriptive and differentiated sensory characteristics. Therefore, it has greater potential in sensory analysis, new product development and marketing in the future alcoholic beverage industry.

### 2.2. Dynamic sensory analysis

In the early sensory analysis, they were often conducted with static sensory analysis. It does not consider the sensory changes throughout the evaluation process (Etaio et al., 2016). Since it is a dynamic process when people smell or eat, the use of dynamic sensory analysis enables the assessment of small changes in senses over time. This type of approach assigns temporal attributes to sensory perception, and can focus on both changes in specific attributes over the course of evaluation, as well as changes in overall flavor. At present, Dynamic sensory analysis has been used more often in industries such as condiments, beverages and alcoholic beverages (L.-L. Zhang et al., 2018; Gotow et al., 2018; Lytra et al., 2016). As with static sensory analysis, sensory analysis is preceded by sample preparation, assessor determination, test room setting, descriptor lexicon establishment and completion of an ethics protocol and signing of an informed consent form.

#### 2.2.1. Time-Intensity (TI)

TI is an evaluation of the intensity of a single attribute based on changes over time and is the most common method for recording changes in a single sensory attribute over time. It can provide a detailed situation of the intensity of sensory attributes over time through continuous measurements.

TI in sensory analysis applications, specific operations include: ①Assessors need to be trained prior to testing and to prepare references as well as intensity scales in advance for the sensory attributes to be evaluated. ②The assessor evaluates by operating a device capable of expressing the degree, such as a mouse (Pierce-Feldmeyer et al., 2019) or pull ring connected to a monitor (computer or monitor). Using the pull ring as an example (Gotow et al., 2018), first restrict the pull ring to a movable range. The position of the pull ring is output via a sensor, and the data is simultaneously converted into a digital measurement, which is displayed and recorded on a monitor. In practice, FIZZ Software (Biosystemes, Couternon, France) is often used for TI analysis data collection (Pineau et al., 2009; Sokolowsky et al., 2015; Sokolowsky & Fischer, 2012), and some laboratories use their own developed programs (Morais et al., 2014). ③After the assessor has finished tasting, a TI (Time-Intensity) curve can be plotted based on the data obtained from the assessor, enabling to obtain parameters such as the time when the assessor first felt the stimulus, the maximum intensity, the appearance of the intensity maximum and the duration, etc. A one-way analysis of variance (ANOVA) is usually used to compare the curve parameters.

TI combined with the CATA method is used to assess the astringency intensity of the wine (Vidal, Antunez, et al., 2018). Trained assessors from sensory panel first evaluated the total astringency of the wines using the TI and then checked off a CATA questionnaire with terms describing the astringency that had been prepared in advance. A boosted regression trees (BRT) model was developed based on the results of sensory analysis to further analyze the relationship between astringency and phenolic composition of commercial red wines. TI was used to assess the postnasal aroma intensity of two specific aroma attributes (black pepper, smoke) in red wines, while also exploring whether differences in salivary flow and composition had an effect on the release of postnasal aromas from the wines (Criado et al., 2021). Since significant differences in salivary parameters were found between different age groups, different age groups were selected for evaluation.

Compared to static sensory analysis, TI is able to evaluate changes in sensory attributes of samples during the sensory analysis process. However, the TI method focuses on one sensory attribute at a time for sensory analysis, so it can only evaluate a small number of sensory attributes or a small number of samples.

#### 2.2.2. Temporal Dominance of Sensations (TDS)

The sensory analysis often involves a large number of samples as well as the evaluation of multiple sensory attributes. The use of TI consumes a lot of time, and the continuous use of TI produces a “halo-dumping” effect (Clark, 1994). Therefore, Pineau et al. proposed the method called TDS (Pineau et al., 2009). TDS is a temporal multidimensional dynamic sensory analysis method. The TDS provides the assessor with a list describing the attributes of the sample and obtains a dynamic multi-attribute sensory analysis result by the assessor selecting the perceptions they consider dominant at each moment of the tasting. TDS is conceptually as temporal as TI and as multidimensional as QDA, while TI is as intense as QDA (Schlich, 2017).

TDS in sensory analysis applications, specific operations include: ①The list of sensory attributes to be evaluated is prepared in advance and displayed on the computer screen. ②The assessor starts the tasting while pressing the "Start" button on the computer screen. ③The assessor chooses the dominant attribute of each moment based on their own senses. Each attribute can be selected multiple times or not selected during the evaluation process. ④The evaluation continues for a period of time until the assessor no longer senses any attributes. The assessor will press the "Stop" button to end the evaluation. ⑤The TDS curve (Standardized Time-Dominance rate) was plotted based on the assessor's evaluation results. TDS, like TI, often uses FIZZ Software for data collection, in addition to the software often used TimeSens Software (Dijon, France), SensoMaker (Lavras, brazil) and others (Ana Carla Marques Pinheiro et al., 2013; Morais et al., 2014; Paz et al., 2021).

TI and TDS were used to analyze the temporal characteristics of the pungency intensity of Baijiu with different aging times, and the subqualities of pungency was also analyzed (Y. He et al., 2021). The TI and TDS results showed no significant differences in the pungency of some of Baijiu samples. However, the TDS results showed significant differences in the dominant subqualities and their duration between the white wines aged for different times. Therefore, the pungency during the assessment is not fully characterized by evaluating the pungency intensity alone. The dynamic sensory analysis was also compared with the results of the descriptive analysis(DA) evaluation, which showed more dynamic and temporal information about the pungency differences in Baijiu.

TDS was also used in consumer research, for example to find out how consumers felt about Blonde Ale and Catharina Sour with elderberries (Machado et al., 2023). According to the TDS curve, it can be seen that red fruits are the dominant attribute for a longer period of time. During sipping, perception changes over time, ending with bitterness, hops and yeast attributes dominating. Finally, TDS was combined with preference to further understand consumer preferences between the two different added beers.

Compared with static sensory analysis, dynamic sensory analysis has a clear advantage in the evaluation results because of the increased influence of time on the senses. However, the fact is that static and dynamic sensory analysis do not provide the same information, so dynamic sensory analysis is not a substitute for static sensory analysis (Di Monaco et al., 2014). Instead, dynamic sensory analysis is used to supplement the data of static sensory analysis, which can better reflect the process of sensory changes during the sensory analysis.

## 3. Intelligent Sensory Technology

There is a certain subjectivity in the application of human sensory analysis in beverage alcohol. Due to the special nature of beverage alcohols, when conducting tastings with large sample sizes, assessors can easily paralyzed by the effects of alcohol on nerves, resulting in increased unreliability and reduced reproducibility of sensory analysis data. Therefore, there is a need to seek an intelligent instrument that can replace human for sensory analysis.

So far, intelligent sensory instruments that mimic human sensory organs have been widely used in fraud detection, property characterization, product identification (Roy & Yadav, 2022; Shi et al., 2022; Xie et al., 2016), etc. Although different intelligent sensory instruments mimic different human organs, their structural components and working principles are similar, all including sensors, signal collectors and computer systems (Lu et al., 2022). The application of intelligent sensory instruments reduces the labor cost and time cost of forming a professional evaluation panel compared to artificial sensory analysis. Intelligent sensory instruments that are currently used more frequently are electronic nose and electronic tongue.

### 3.1. Electronic Nose (E-nose)

The electronic nose consists of a gas transmission system, a multi-sensor array system, and a signal processing system. Signal processing includes data preprocessing and pattern recognition systems. When a specific volatile substance exceeds its threshold, the sensor is able to detect the substance and form a signal related to its concentration for transmission to a computer, which is pre-processed (by filter) to eliminate noise interference due to environmental factors and sensor drift, and then analyzes and classifies it through a pattern recognition system (Wei et al., 2023).

Sensors are the core of the electronic nose and are mainly implemented by metal oxide semiconductor sensors (MOS), metal-oxide-semiconductor field-effect transistors (MOSFET), conductive polymer sensors, quartz microbalance sensors (QMB), and other sensors to achieve (Yakubu et al., 2023). The sensor determines the overall effect of the e-nose to a certain extent, so the selection of the sensor is very important. In order to obtain more gas information, arrays containing sensors with different sensitivities are often used. However, simply increasing the number of sensors can lead to an increase in the amount of excess data collected, which in turn affects the recognition of the electronic nose (Peng et al., 2023).

Pattern recognition is also an important part of the process of gas identification by the electronic nose. Pattern recognition is a way to identify gases by quantifying the collected data, data analysis, feature extraction and classification decision (Fig. 4). Data quantification refers to the transformation of the collected gas information into the symbols of computer operations. Data analysis is the processing of data, including the removal of outliers and the elimination of noise. One of the common methods for feature extraction is dimensionality reduction. The most commonly used methods are principal component analysis (PCA) and linear discriminant analysis (LDA) (S. Feng et al., 2019). Finally, categorization is then done through classification decisions. Pattern recognition usually requires building a decision model first and evaluating the performance and accuracy of the model through testing before it can be used. The more common recognition algorithms include PCA, LDA, support vector machines (SVM) (Pardo & Sberveglieri, 2005), k-nearest neighbor (KNN), random forest (RF) (Juan, & Rodríguez, L. I. K., 2006) and so on. In addition to this, neural network-based algorithms are also a hot topic of current research, including back propagation neural network (BPNN) (Aguilera et al., 2012), radial basis function neural network (RBFNN), and convolutional neural network (CNN), etc. Different recognition algorithms have their own advantages, in the selection should be based on different needs to choose the appropriate algorithm. For example, the differentiation of different types of alcoholic beverages and the identification of different brands of similar alcoholic beverages can be chosen in different ways to obtain more accurate results.

E-nose in sensory analysis applications, specific operations include: ①The test sample is filled in a certain amount into a headspace vial or sealed vial. ②Choose the appropriate equilibrium temperature and equilibrium time so that the aromas reach equilibrium in the upper part of the vial. ③Basic information such as acquisition time, cleaning time, interval time and carrier gas flow rate are set according to experimental

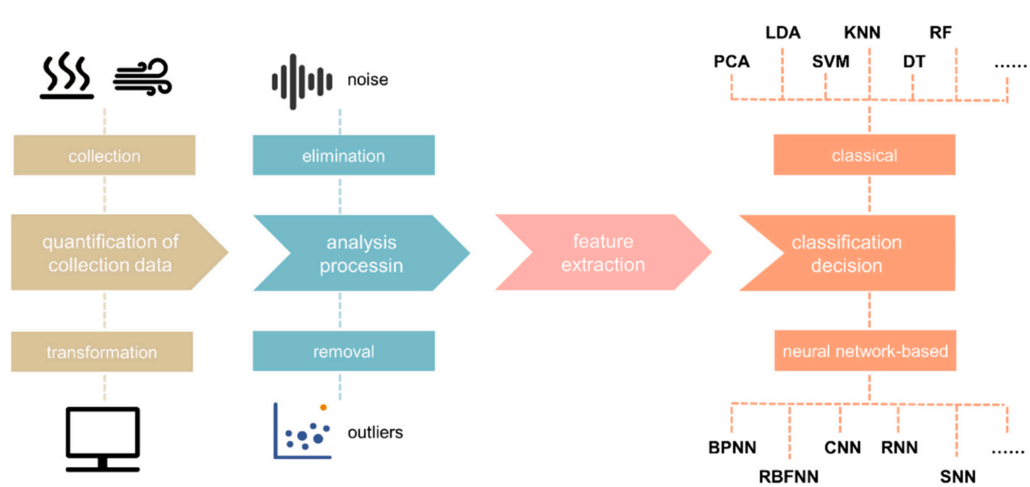



**Fig. 4.** . Main steps of pattern recognition. (PCA: principal component analysis; LDA: linear discriminant analysis; SVM: support vector machines; KNN: k-nearest neighbor; DT: Decision Tree; RF: Random Forest; BPNN: Back Propagation Neural Network; RBFNN: radial basis function neural network; CNN: convolutional neural network; RNN: recurrent neural network; SNN: spiking neural network)

needs. ④Insert the collector into the vial, avoiding touching the bottle wall and the sample. ⑤Waiting for the end of the acquisition time, the computer displays the complete signal image synthesized from the sensor signal. ⑥The class attributes of the samples are determined by pattern recognition methods (Tan & Xu, 2020).

The aroma and color of 14 commercially available kiwifruit wines were assessed using an intelligent sensory instrument and GC-MS (Lan et al., 2022). Aroma evaluation using an electronic nose with built-in MOS. The analysis of the e-nose data by LDA enabled the differentiation of different odor characteristics of the samples and the results were relatively consistent with the GC-MS findings. In practical applications, the same attention is given to achieving faster and more accurate analysis. (Rodriguez Gamboa et al., 2019) used a self-developed e-nose based on commercially available sensors to monitor wine quality. The electrical signals of wine samples with different levels of spoilage collected by the electronic nose were compared. And by comparison, it is found that the data processing with deep multilayer perceptron (MLP) classifier is substantially faster than the traditional SVM classifier method in terms of prediction speed. The method processes the data with a deep MLP classifier can get the valuation in 2.7 seconds of gas injection for fast detection. (Yang et al., 2020) used the MOS-based E-nose combined with pattern recognition to distinguish 16 wines from Baijiu. The results show that PCA misses aromatic details when distinguishing between different wine categories. Therefore, this study established a transfer-learning framework based on BPNN, which can identify wines of different categories with good accuracy.

The disadvantage of the electronic nose is that it does not allow qualitative quantification of the individual compounds present in the sample. (Wisniewska et al., 2016) used e-nose based on ultra-fast gas chromatography for the rapid analysis of vodka and whisky. Due to the built-in column, a single compound can be identified. Compared to traditional electronic noses with built-in sensors, this method is able to accomplish both the classification of spirits and the determination of the composition of the sample. The electronic nose has the advantages of no damage to the sample structure, rapid detection, and small sample size. At the same time the electronic nose is also moving in the direction of more portability. The field of e-nose sensor optimization (F. Han et al., 2020) and the combination of e-nose and pattern recognition techniques (Rahman & Charoenlarpnopparut, 2015) continues to evolve, with more optimized materials and data analysis models constantly emerging.

### 3.2. Electronic Tongue (E-tongue)

The structure of the electronic tongue is similar to that of the electronic nose, which is consists of a sampler, a sensor, and a signal processing system. Like the electronic nose, the sensor is at the core of the electronic tongue and is realized by electrochemical, optical, mass or biological sensors. The most common electronic tongues are measured using the potentiometric and voltametric methods (W. Wang & Liu, 2019). The built-in potentiometer electronic tongue is measured according to the different electrode potentials between the outer membrane boundary of the sensor and the reference electrode. However, voltammetric method uses electrode potentials to drive electron transfer, which is measured by measuring the resulting current (Jiang et al., 2018). The electronic tongue imitates the human taste system and is able to recognize and distinguish the five basic tastes: sweet, sour, salty, bitter and fresh (Ross, 2021). Analysis by electronic tongues can eliminate the potential dangers posed to humans by sensory analysis, and thus electronic tongues has potential in food quality and safety research (Mahdi Ghasemi-Varnamkhasti et al., 2018).

Electronic tongue in sensory analysis applications, specific operations include: ①Prepare the solutions required for the test, including samples, control solutions, and cleaning solutions. Among them, the sample needs to be selected as a clarified and stable state liquid sample, so the solid sample needs to be processed before use. ②Set up the measurement program. Set parameters such as the frequency of sensor and reference electrode cleaning, the cleaning time and the sample collection time. ③The electronic tongue tests the sample, and then measures the aftertaste information after the test is complete (Zheng et al., 2023). ④When the measurement time is over, the computer displays a complete image of the signal synthesized from the sensor signal. ⑤The measurement data is analyzed by the method of pattern recognition, and the common method is the same as the electronic nose.

The voltammetric sensor e-tongue was used to analyze wines. The effect of oak barrels on wine and the prediction of wine maturity were measured separately, and qualitative and quantitative models were constructed using LDA and partial least squares (PLS) (Ceto et al., 2017). In the identification measurements of whether oak barrels were used or not, the respective rates reached 100%. E-tongues of a potentiometric chemical sensor were used to measure defective components in wines, while original and adulterated wine samples were also identified (Lvova et al., 2018). The results showed that the electronic tongue was 71% correct in distinguishing these wine samples and was able to accurately monitor compounds above specified allowable levels. E-tongues with self-fabricated electrodes were also used to identify rice wine of different vintages (H. Zhang et al., 2020). The results showed a high correlation between the collected data and the year of aging, and that the samples contained Tyr, AA and Glu above their detection limits, but it was difficult to obtain their exact concentrations. Therefore, the acquired feature data is difficult to use as data input for pattern recognition.

In fact, there are limitations to using a single method for flavor analysis. The electronic nose and electronic tongue were used separately and in combination to differentiate the different samples (Haddi et al., 2014). The comparative analysis of the data revealed that while separate use can capture features between different samples, it does not completely distinguish between all samples. By using a combination of data fusion, the different samples can be distinguished more efficiently and accurately.

The study found that the e-tongue was able to distinguish defective wines before trained sensory evaluator could assess that the wine was showing spoilage (Paup et al., 2021). Thus e-tongue has advantages in the field of monitoring the quality and safety of alcoholic beverages. At present, the electronic tongue sensor is also constantly updated. Now, new biosensors have been developed with nanomaterials, which can simplify the measurement method and make the measurement faster and more accurate (Loira et al., 2020).

## 4. Innovative Techniques in Sensory Analysis

Intelligent sensory instruments are relatively more objective in sensory analysis, while reducing the human and time costs of recruiting and training professional assessors, but instruments lack descriptions of specific sensory attributes. Whereas artificial sensory analysis can obtain the specific sensory attributes of the product more completely in practical applications, and consumer testing needs to rely on the human senses to be conducted. However, sensory analysis relies on assessors' responses, so different participants (assessors) may have different biases during the sensory analysis due to physical and psychological factors (Köster & Mojet, 2015), which may lead to biased test results (D. D. Torrico et al., 2018). Using implicit methods of measurement avoids the limitations of explicit methods. Explicit methods obtain their test results through participants' self-report. While implicit methods use biometric techniques (including facial expressions, heart rate, skin conductance, body temperature, eye tracking and electroencephalogram) to understand the complex human emotions (Schouteten, 2021) in sensory tests using biological responses that accompany emotions and thus explain participants' behaviors and preferences. In short, implicit measurement attempts to capture unconscious emotional responses and reduce the bias introduced by participants' subjective expressions.

Olfactory is primarily the perception of the gas through the orthonasal and retronasal route (Han & Hummel, 2019). The orthonasal route is that odor components are inhaled through the nasal passages, combined with the olfactory receptors, and the resulting electrical signals that are transmitted to the cerebral cortex, to form olfactory perception. The retronasal route is to process food through the oral cavity, and the released odor components are combined with the olfactory receptors through the retronasal pathway, and the electrical signals are transmitted to the cerebral cortex.

The basic unit of taste perception is a taste bud, which are composed of receptor cells and supporting cells (Wang et al., 2024). Taste receptor cells (TRC) are divided into four main types. When taste substances are dissolved in saliva and spreads to the taste bud cells, the five basic taste components (sour, sweet, bitter, salty, and umami) are combined with their corresponding receptors, neurotransmitters are released, and the resulting electrical signals are transmitted to the nerve center, and taste is generated in the cerebral cortex (Roper & Chaudhari, 2017) (Fig. 5).

In food sensory analysis, odor and taste are two important factors that affect flavor. However, they do not only affect the flavor of food in an independent way. The brain integrates olfactory signals as well as gustatory signals during eating, where cross-modal perceptual interaction is also critical to overall flavor. The taste-odor interaction has been used in a number of 'reduce the salt' and 'reduce the sugar' (Oliveira et al., 2021) practical situations.

Therefore, it is feasible to further explain the complexity of human emotions in sensory evaluation by monitoring the brain. With the development of technology, biometrics has also received more attention in the food field (S. R. Jaeger et al., 2017). However, the use of biometrics is not intended to completely replace traditional manual sensory analysis, but rather to improve the quality of data by using biometrics in combination with manual sensory analysis, and thus to understand the participants' evaluation of food more effectively and accurately.

In a further consumer tests of mixed berry juice, (Waehrens et al., 2018) added emotion words to the CATA questionnaire and found a link between sensory characteristics and emotional responses and preferences. Different sensory attributes can elicit different emotional expressions. 2016, (Beyts et al., 2017) used a beer with low aroma intensity as the base beer, to which a food-grade flavor capsule was added, and subjects were allowed to perform sensory analysis while their heart rate, skin temperature, breathing, and facial expressions were recorded. The results showed that heart rate and skin temperature were not affected by the sample aroma, in contrast to facial expressions which responded significantly to the aroma. This may be because some physiological measures appear to have limited sensitivity in distinguishing between similarly pleasing products (Pichon et al., 2015), and therefore only electroencephalogram (EEG) and facial expression techniques are discussed in this study.

### 4.1. Electroencephalogram (EEG)

The cerebral cortex is the highest level nerve center that can evaluate stimulation from various organs. When the human senses are stimulated, neurons located in the corresponding perceptual areas of the brain are activated. The EEG signal is the change in voltage fluctuations generated by the ionic movement of neurons in the brain (MacDonald, 2015). When EEG records the biological potential signal of changes in brain nerve signals caused by changes in olfactory and taste, it can objectively reflect the brain activity under the stimulation of different odors and tastes.

EEG is a useful technique to support traditional sensory analysis. It is used to study consumer preferences because of its non-invasive nature, high temporal resolution, portability and relatively low cost (Domracheva & Kulikova, 2020). Measures of brain activity are good implicit indicators of emotion testing when people are unable to express their preferences.

In sensory analysis applications, subjects are required to sit in a chair with a conductive medium attached to their scalp, and their brain waves before, during, and after exposure to the stimulus are obtained through acquisition instruments and specific signal processing methods of analysis (Songsamoe et al., 2019).

Beer experts, assessors and non-professional consumers were convened to participate in the sensory analysis of beer (Hinojosa-Aguayo et al., 2022). They were asked to rate the beer according to its

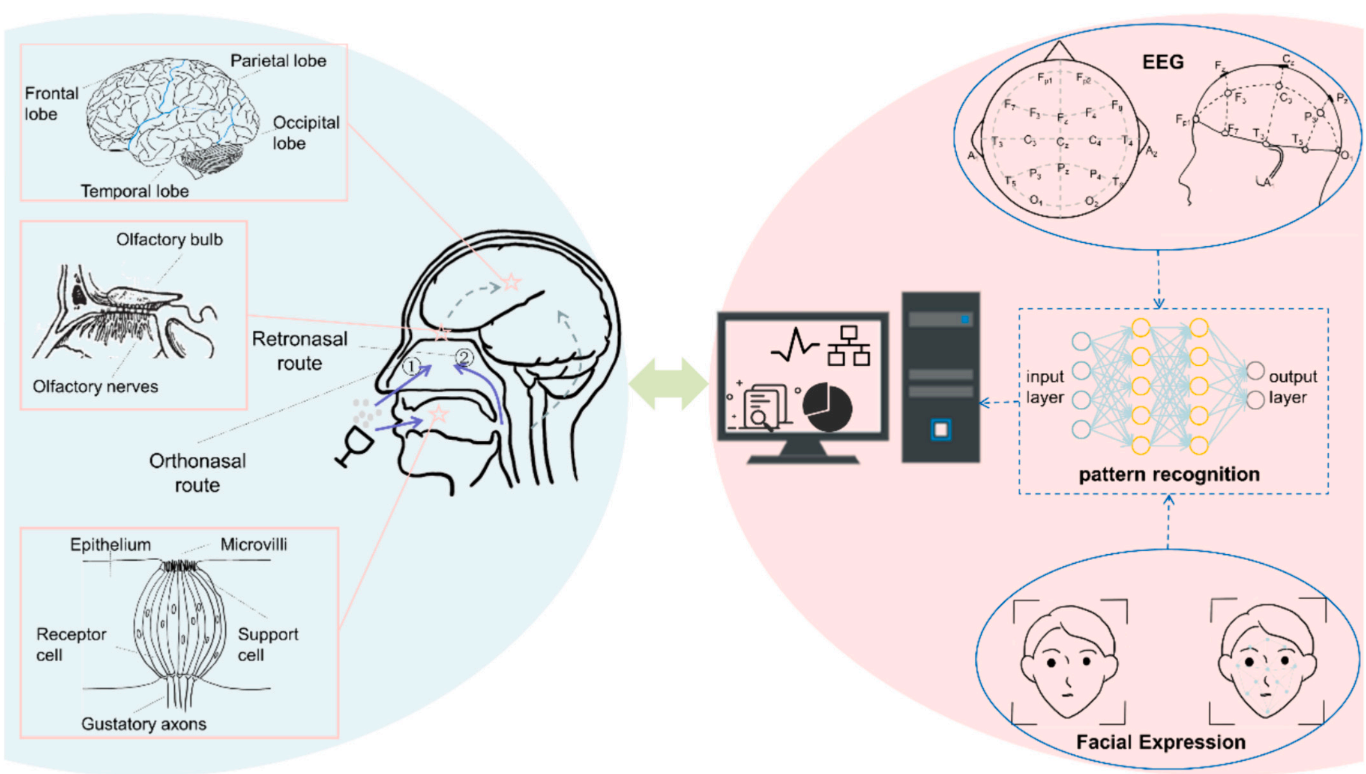



**Fig. 5.** . Human sensory mechanisms in traditional sensory analysis and the mechanisms of sensory analysis methods relying on modern technology

sensory attributes and hedonic value of beer, and recording their brain activity. The results showed some differences between experts and consumers in their ratings of sensory attributes, however relatively small differences were detected in their brain activation levels. It was also found that beer experts showed a better fit between explicit judgment and implicit measurement of beer sensory and hedonic quality. Consumers are limited by professional knowledge and have not experienced extensive training in rating sensory attributes (Honoré-Chedozeau et al., 2019), so the use of EEG technology can assist consumers in sensory analysis. (C. Gonzalez Viejo et al., 2019) had consumers assess the foam, color, aroma, taste, flavor and overall acceptability of the beer using the 9-point hedonic scale, while obtaining EEG signals from consumers during sensory analysis. When the brain waves get different frequencies, it means that the brain is in different states. For example, when the brain wave θ signal is strong, the human brain is in a state of intuition, creation and recall. Therefore, when consumers feel more bitterness in the beer than the feeling of liking it, the consumer will be more intuitive and recall more information. Thus θ signal was positively correlated with bitterness. A combination of traditional sensory analysis and emerging technologies led to the conclusion that consumers prefer beers with higher foam and lower bitterness.

Some studies have also emerged that combine raw data captured by EEG with emotional data to build an index model of the preference for a comprehensive emotional experience based on the accumulation of the database. This is used to synthesize the preferences of the participants. However, the model approach is currently not widely used. In addition to being directly used by consumers in the sensory evaluation of a sample, EEG is also currently used to construct perceptual models of different flavors for flavor discrimination (Cui et al., 2023).

Compared with other neuroimaging techniques (including fMRI, fNIRS, etc.), EEG has less expensive and an intrinsic property that characterizes, for example, the intensity of a perceived odor or taste. However, EEG only shows the EEG signal (frequency) and does not identify the exact location of brain activity (P. Han, 2021).

### 4.2. Facial Expression Analysis

Some facial expressions in humans are not under individual control, so facial expressions, like EEG, have been used as implicit methods to measure subjects' emotional expression in response to food stimuli (W. He et al., 2016). Numerous studies have shown that human facial expressions can convey information about a person's emotions, and that specific facial muscle changes can express the affirmation of sensory pleasure or disgust of sensory discomfort (Walsh et al., 2017).

In sensory analysis applications, a high-definition camera is required to capture facial expression information during the evaluation process. In the test, data on the facial expressions of the subjects were collected throughout the sensory analysis process of resting, sniffing, tasting, filling out questionnaires, and gargling. Specific software is then used to record and analyze facial expressions according to the seven basic human emotional expressions (Anger, Contempt, Disgust, Fear, Joy, Sadness, Surprise) (Samant & Seo, 2020). For example, the FaceReader software (Claudia Gonzalez Viejo et al., 2018) can recognize the collected facial information, establish a three-dimensional facial model, mark the muscle key points, and finally classify the collected information in the expression image database to determine basic type of emotion.

A high-resolution camera was used to capture 20 facial expressions and 7 basic emotions of the consumers while tasting beer samples, and had the consumers fill out a preference questionnaire at the end of the experiment (Wakihira et al., 2022). The test data showed that it is feasible to use facial expressions to analyze the consumer behavior of consumers during beer tasting. Among the 20 facial expressions measured, "lip suck" and "lip press" were potentially effective facial expression indicators for predicting beer choice after tasting. The "lip suck" before swallowing has a negative effect on preference, while the "lip press" after swallowing has a positive effect. An integrated camera system was used to capture thermal images and record video of assessors while tasting beer (C. Gonzalez Viejo et al., 2019). FaceReader was used to analyze the video and corresponded to different emotions based on the changes in facial expressions. By comparing facial expressions as well as body temperature, it was found that disgust was positively correlated with body temperature.

Changing emotions can be quickly captured through facial expressions and subconscious emotional expressions can be analyzed (van Bommel et al., 2020). However, the method is limited by the shooting environment, the resolution and sensitivity of the camera (Leitch et al., 2015). And the large amount of data collection can be cumbersome for data processing. There is still room for improvement in the application of facial expressions in the field of consumer preference testing. Future advances in equipment and improved operating procedures could provide greater assistance in data accuracy.

## 5. Conclusion

This work provides a comprehensive review of the specific methods and applications of sensory analysis. In general, the use of sensory analysis methods in the alcoholic beverages industry was reviewed and prospected from three aspects including artificial sensory analysis, intelligent sensory technology and innovative techniques. Artificial sensory analysis is a human-based analysis method, while intelligent sensory technology is a sensory analysis using only instruments without human participation. Innovative techniques in sensory analysis are based on the evaluation of human subjects, but do not require human self-reporting but rather biometrics to obtain data. Based on continuous optimization and improvement, different sensory analysis methods and various combined sensory analysis methods have been successfully applied to quality control and flavor analysis of alcoholic beverages. However, different types of sensory analysis have certain drawbacks. Artificial sensory analysis still needs to be optimized in a continuous process to meet more analysis needs. Intelligent sensory technology still needs to be improved in both sensors as well as pattern recognition methods to achieve higher sensitivity and accuracy. Innovative techniques in sensory analysis will need to be refined in the future in order to find a better system. The interest in the use of different sensory analysis methods in alcoholic beverages is still increasing. This method need to be constantly updated and improved according to the changing needs of analysis. Therefore, in order to provide more convenience for the alcoholic beverage industry, it is still the current trend to continuously explore more advanced and applicable methods. This work provides a reference for the selection or optimization (including combination or adjustment) of sensory analysis methods for the alcoholic beverage industry in the future.

## CRediT authorship contribution statement

**Jing Wang:** Investigation, Data curation. **Lina Qiao:** Visualization, Investigation. **Ning Zhang:** Writing – review & editing, Supervision. **Baoguo Sun:** Supervision. **Hehe Li:** Resources. **Jinyuan Sun:** Resources. **Haitao Chen:** Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

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