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Review

# Emerging Sensory Methodologies to Support Strawberry Breeding and Future Prospects Combined with Augmented Reality

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**Abstract:** Strawberry production has been continually increasing worldwide, but this growth has often resulted in a lack of taste, favoring yield and plant adaptability instead. However, in recent decades, consumer focus has shifted towards more flavorful fruits. Consequently, the application of new sensory methodologies for consumers in strawberry breeding programs is becoming essential. This review provides an overview of new rapid consumer-based sensory methodologies and a brief summary of their potential applications when combined with Augmented Reality technology. These advancements aim to better understand and meet consumer needs, offering breeders valuable tools for their future work.

**Keywords:** strawberry; breeding; sensory evaluation; rapid sensory evaluation; consumer; augmented reality

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## 1. Introduction

Strawberry production exceeded 9.36 million tonnes in 2021, with Asia being the main continental producer (4.48 million tonnes), followed by the Americas (2.22 million tonnes), Europe (1.76 million tonnes), Africa (827.21 thousand tonnes), and Oceania (59.72 thousand tonnes) [1,2].

Over the last half-century, strawberry breeders have primarily focused on meeting consumer demand by ensuring a consistent year-round supply of large-sized fruits at affordable prices. This emphasis has led breeders to prioritize traits such as high yield, large fruit size, enhanced disease resistance, ease of harvesting, and adaptability to various pedoclimatic conditions across different countries. However, this intense focus on quantity and convenience has often come at the expense of flavor and nutritional quality. While previous varieties excelled in production metrics, their sensory and nutritional attributes suffered. In recent years, there has been a notable shift in consumer preferences towards prioritizing sensory and nutritional quality over sheer quantity. Consumer attraction today is primarily driven by color, odor, and taste. However, thanks to the continuous increase in health awareness, nutritional aspects, such as antioxidant levels, vitamin C, and mineral content, are also becoming important [3–7]. Consequently, breeders are now directing their attention towards developing varieties that not only offer high yields and robust physical characteristics but also exhibit superior sensory and nutritional qualities [8–10]. Consumers particularly value sweetness when it comes to strawberries, although aroma also significantly influences overall appreciation. Volatile compounds responsible for fruity, floral, and sweet aromas play a crucial role in enhancing consumer acceptance of the fruit. Given the importance of these sensory factors, it is clear that incorporating sensory information into breeding programs is essential for breeders to align more closely with consumer preferences and meet their evolving needs [11].

## 2. Sensory Evaluation and Breeding

Sensory evaluation in breeding programs is often conducted without following proper guidelines [6]. Typically, the sensory characteristics of advanced selections and new cultivars are assessed by a small number of people, sometimes by the breeders themselves. This usually leads to subjective information and personal preferences [6,12–14]. The strawberry is a very complicated product in relation to its sensory aspects [7] because of its variability and high sensitivity to environmental conditions (temperature, light exposure, and humidity). Additionally, the strawberry is a very perishable fruit (1–2 days) [15–18]; hence, a standardized methodology is needed to avoid further variability.

Traditionally, strawberry sensory evaluation applies descriptive analysis, which involves trained assessors, usually 8–20, selected and trained based on superior sensory acuity and the ability to discriminate among products. This method provides detailed, reliable, and repeatable information [6,19,20]. However, due to the high time, resource, and cost demands of this method [11], combined with the large volume of material that breeders periodically evaluate, this methodology is difficult to apply. This review aims to provide an overview of new rapid sensory methods that can be used as alternatives to traditional descriptive analysis. The described methods can potentially improve and optimize material selection during the advanced stages of strawberry breeding in the future.

## 3. New Rapid Sensory Test

In the past 10 years, sensory professionals have shifted their focus towards rapid methodologies involving untrained panelists [4]. But what exactly does 'rapid' means in this context? How can the results from untrained panelists be comparable to those obtained from trained ones? These tests are considered rapid because they rely on consumer-based assessments, eliminating the need for recruiting, training, and retaining judges [21]. Recent studies, particularly in the field of strawberries, have shown that these new rapid methodologies can be considered a valid alternative to traditional sensory profiling [6,11,17,21–23].

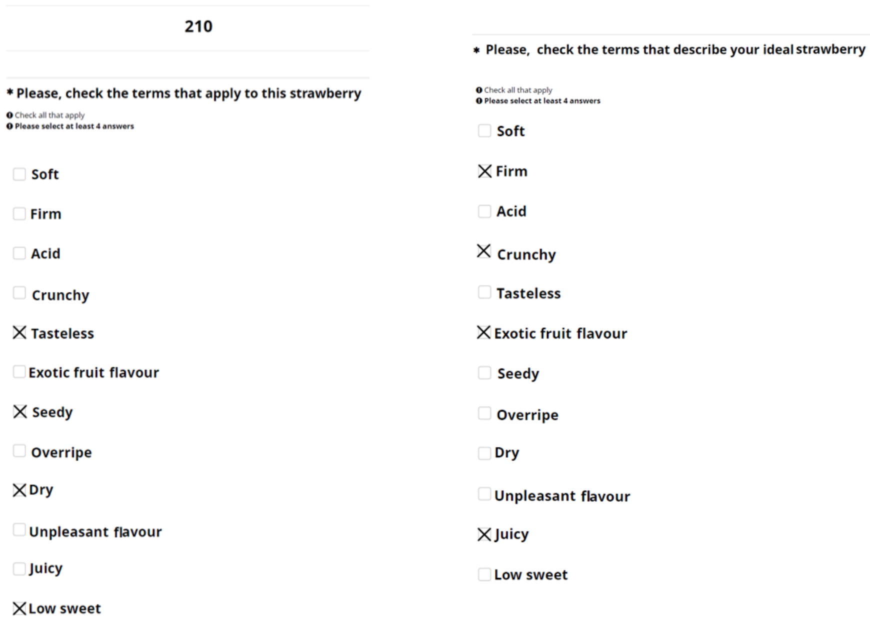
Rapid methodologies in sensory evaluation are typically categorized into two main classes based on their approach: specific attribute methodologies and holistic methodologies. Specific attribute methodologies concentrate on evaluating individual sensory attributes of products, while holistic methodologies assess overall similarities or differences among products [22].

### *3.1. Specific Attribute Methodologies*

#### 3.1.1. Check All That Apply (CATA)

Check-All-That-Apply (CATA) questionnaires are widely used in marketing research. However, they have recently also gained popularity in sensory science to collect direct feedback from consumers. CATA is a versatile multiple-choice format that asks participants to select from a list of words or phrases the options that best describe the product (Figure 1a) [23–26] while they taste the product. Since CATA relies on specific attributes, careful selection of terms is crucial during the design phase. The terms used should be easy to understand, be related to common vocabulary for consumers, and avoid synonyms [22]. Ideally, the list should contain between 12 and 30 terms. Shorter lists may encourage consumers to use all the terms provided, resulting in decreased discrimination among samples. Conversely, longer lists may overwhelm participants, causing them to only select the first options without considering all the sensory characteristics of the product [22,27].

Randomization of the terms' order is necessary to avoid bias in the results, as terms at the top of the list tend to be selected more frequently than the others [22,23]. The number of products may vary from 1 to 12 depending also on the aim of the study. The CATA participants' number may depend on the final goal; however, fewer than 60 respondents are discouraged in relation to statistical validity, especially if the differences in the product assessed are not well defined. When CATA is combined with hedonic evaluation, the number of consumers required increases to 100–120. If consumer segmentation is desired, even more consumers are needed, potentially several hundred [22,23].




(**a**) (**b**)

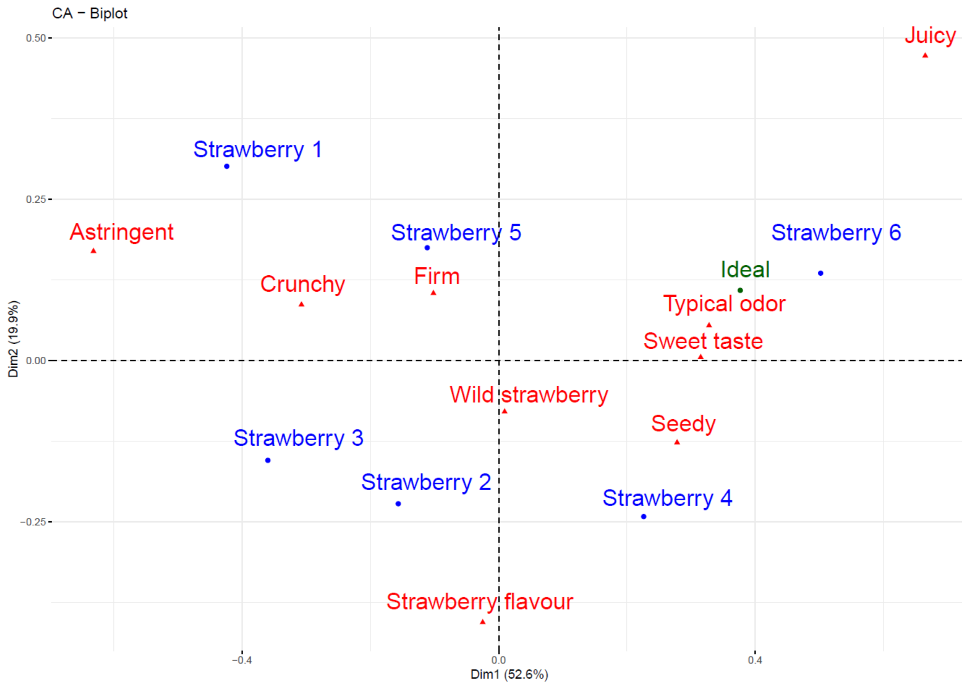
**Figure 1.** Example of CATA list of attributes provided in a strawberry consumer test. (**a**) CATA attributes describing the sample (210). (**b**) CATA attributes describing the ideal product.

Thanks to this high versatility, CATA may be used also to collect different information than sensory characteristics from consumers, such as emotional response, consumption experience, or marketing cues [4].

CATA questionnaires can also be used to assess the ideal product in parallel with overall liking evaluations, which are typically measured using a hedonic scale. In this test, participants first rate their liking of the product using a hedonic scale, usually a 9-point scale. Participants then use CATA questionnaires to assess the sensory characteristics of the products. Following this step, participants repeat the CATA questionnaire once again, but this time to describe their ideal product (Figure 1b). In this way, the ideal product can be used as a supplementary sample to determine which sample is the most appreciated and similar to the ideal product (see Figure 2a below). In the past decade, CATA methodology has been successfully applied in various studies for evaluating strawberry breeding selections [11,19,28].

The CATA outcome consists of binary data that indicate if the respondent has selected a term or not. The data are collected in a matrix in which there are as many columns as the attributes in the CATA questionnaire. The data are usually summarized in a contingency table that contains the number of consumers selecting that given attribute for each sample (Table 1). The data may be displayed as counts or percentages and may be used to identify the most relevant terms used for describing samples. To evaluate significant differences among samples, Cochran's Q test can be applied to each attribute individually [23,29].

A further statistical elaboration, Correspondence Analysis (CA), can be applied to enhance the results' interpretation. CA is a statistical method in the contingency table, enabling the visualization of rows and columns in low-dimensional space. CA hence allows the generation of a sensory map explaining how the attributes characterize products. Similar to Principal Component Analysis, CA displays the data from the contingency table in orthogonal dimensions to explain as much variance in the experimental data as possible (Figure 2a) [23,29].

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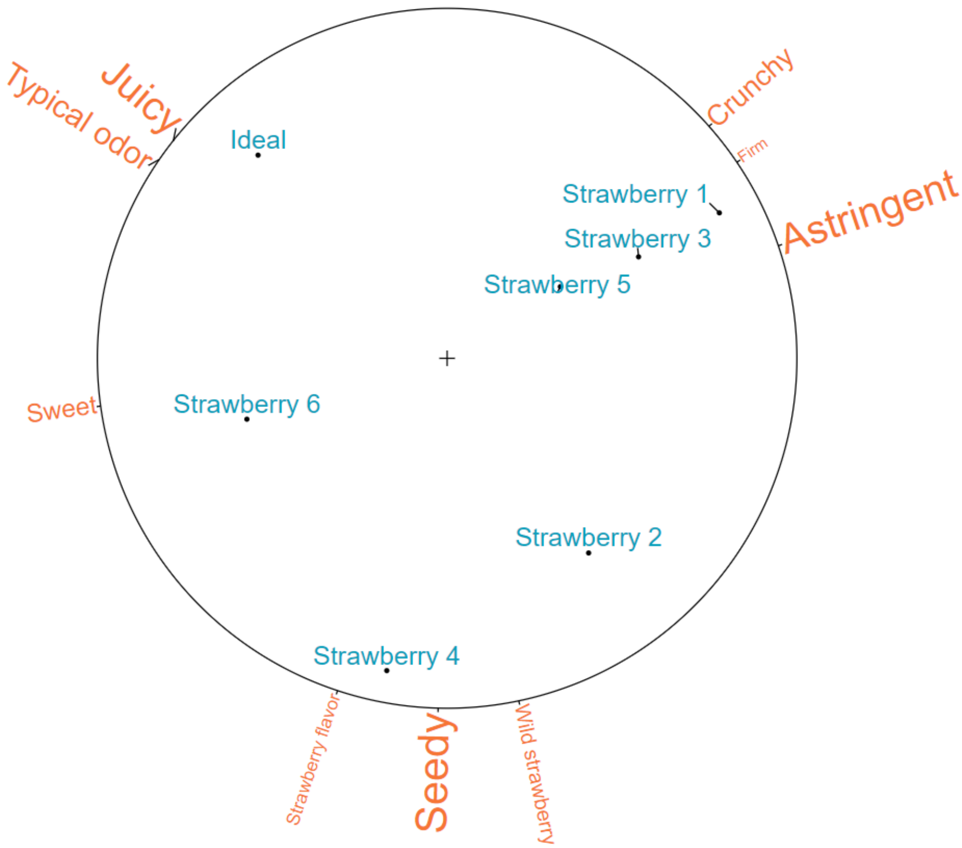



(**b**)

**Figure 2.** Example of correspondence analysis describing CATA results of six strawberries plus the ideal product considered as a supplementary sample. (**a**) CA shown with a classic scatter plot. (**b**) CA shown with an alternative moon plot to overcome reading problems.

**Table 1.** Example of CATA contingency table containing the count of participants who select the attribute for each strawberry sample and the ideal product.

| Sample | Strawberry Flavour | Sweet Taste | Juicy | Firm | Astringent | Typical Odor | Seedy | Wild Strawberry | Crunchy |
|---|---|---|---|---|---|---|---|---|---|
| Strawberry 1 | 13 | 9 | 13 | 64 | 60 | 15 | 25 | 34 | 73 |
| Strawberry 2 | 74 | 30 | 9 | 32 | 63 | 24 | 52 | 76 | 49 |
| Strawberry 3 | 68 | 14 | 4 | 41 | 44 | 24 | 14 | 32 | 78 |
| Strawberry 4 | 63 | 63 | 10 | 59 | 8 | 31 | 66 | 42 | 44 |
| Strawberry 5 | 30 | 71 | 22 | 41 | 72 | 26 | 31 | 44 | 62 |
| Strawberry 6 | 56 | 68 | 77 | 56 | 7 | 71 | 73 | 68 | 53 |
| Ideal | 100 | 100 | 82 | 70 | 20 | 100 | 15 | 65 | 73 |

However, the traditional scatter plot used to visualize Correspondence Analysis (CA) can be misleading because the two dimensions of variance (dim1 and dim2) often have different percentages of variance, indicating how much each dimension explains the total variance. This can lead to false interpretations, especially for those not familiar with this type of plot. To overcome this problem, a Moon Plot (MP) may be used [30]. This plot is less susceptible to misinterpretation since the rows are plotted as in CA, but the column points are placed equidistant from the origin in a circumference. The information given by CA through the distance from the origin is substituted by the size of the labels in the MP. Thus, the font size of an attribute in MP represents its influence on discriminating among the samples. An attribute with a larger font size has a stronger influence than one with a smaller font. Just as in CA, an attribute farther from the origin indicates a greater impact (Figure 2b). Reading CA and MP plots is not easy and can lead to misinterpretation, and a deep knowledge of these methods is thus needed [30].

#### 3.1.2. Penalty Analysis (PA)

Combining CATA with the ideal product and overall liking makes it possible to perform a further useful analysis: Penalty Analysis (PA). PA is conducted comparing the results of the assessments of the two (product and ideal product) CATA tests and the overall liking evaluation. PA aims to determine the decrease in liking associated with any deviation between the attributes selected as ideal and those perceived in the real product. To describe the deviation between the ideal and the real product, a dummy variable approach is usually used between the ideal-product CATA and the real-product CATA. By combining in a scatter plot the percentage of attributes perceived as different by consumers and the drop in liking, it is possible to detect which attributes negatively affect the liking of each product (Figure 3) [23,29,31]. PA, based on CATA, has been shown to be a powerful method in breeding programs for understanding which fruit traits are more appreciated by consumers [32], and it has also already been applied to strawberry fruit [33].

In conclusion, the main advantages of CATA and its applications are their rapidity and simplicity of execution. The process of attribute selection is intuitive and does not require a training period or adaptation time. Additionally, the extreme flexibility of the method allows it to be used for various purposes—not just for gathering food traits, but also for exploring emotions and marketing cues. On the other hand, the choice of attributes is crucial and may lead the evaluation in the wrong direction, potentially misrepresenting the products assessed. Another limitation of CATA is that due to its extreme simplicity, it does not encourage a cognitive process in consumers, which carries the risk of an inaccurate product description. Some authors have attempted to solve this by introducing a yes/no answer instead of just checking each term to increase attention during the task [23,25,26].

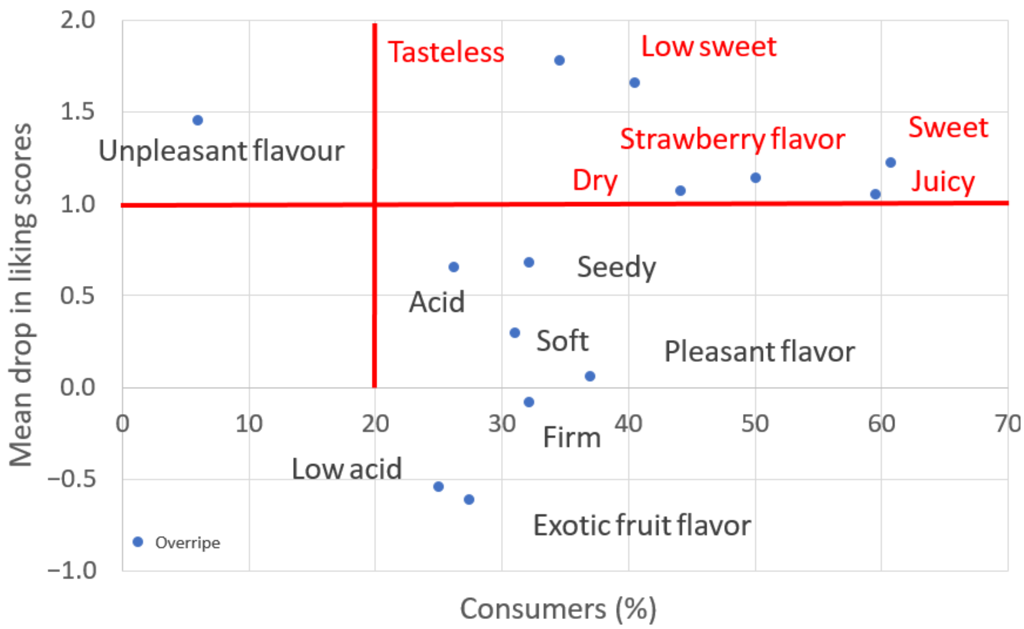



**Figure 3.** Example of PA representation in strawberry. The red attributes in the red square are those that consumers rate as different from ideal with a percentage higher than 20% and that generate an effect of liking mean drop higher than 1 point.

3.1.3. Rate All That Apply (RATA)

RATA is a variant of CATA in which participants are asked to check all the terms that apply to describe the product and then, through a scale (usually a 3- or 5-point scale), are also asked to rate the intensity [34,35]. The intensity rating of the attributes in RATA has the aim of increasing the discrimination of samples with fine differences. Hence, RATA may be preferred to CATA when the products analyzed are similar and differ in sensory attribute intensity. However, if the samples are not so similar, CATA may have a higher discrimination power [23].

RATA data can be analyzed using the usual approach for intensity scales: analysis of variance and Principal Component Analysis (PCA) (Figure 4) [36].

The main advantage of RATA compared to CATA is its ability to gather both quantitative and qualitative responses through the use of scales. This enhances RATA's discrimination power and can yield better results when products are very similar but differ in the intensity of certain attributes. Conversely, the use of scales can be the main limitation of RATA, as they may be tricky and difficult for consumers to understand.

3.1.4. Flash Profile (FP)

The flash profile (FP) within rapid descriptive sensory methodology closely resembles the conventional descriptive analysis profile [21]. Indeed, FP is founded on a quantitative evaluation using sensory attributes.

The test is divided into two main steps. In the first step, consumers are presented with whole products and asked to provide a list of individual terms they believe describe the sensory differences among the products [37]. In the second step, each consumer evaluates the products using the list created in the first step. They rank the products for each attribute, considering their intensity [22,38].

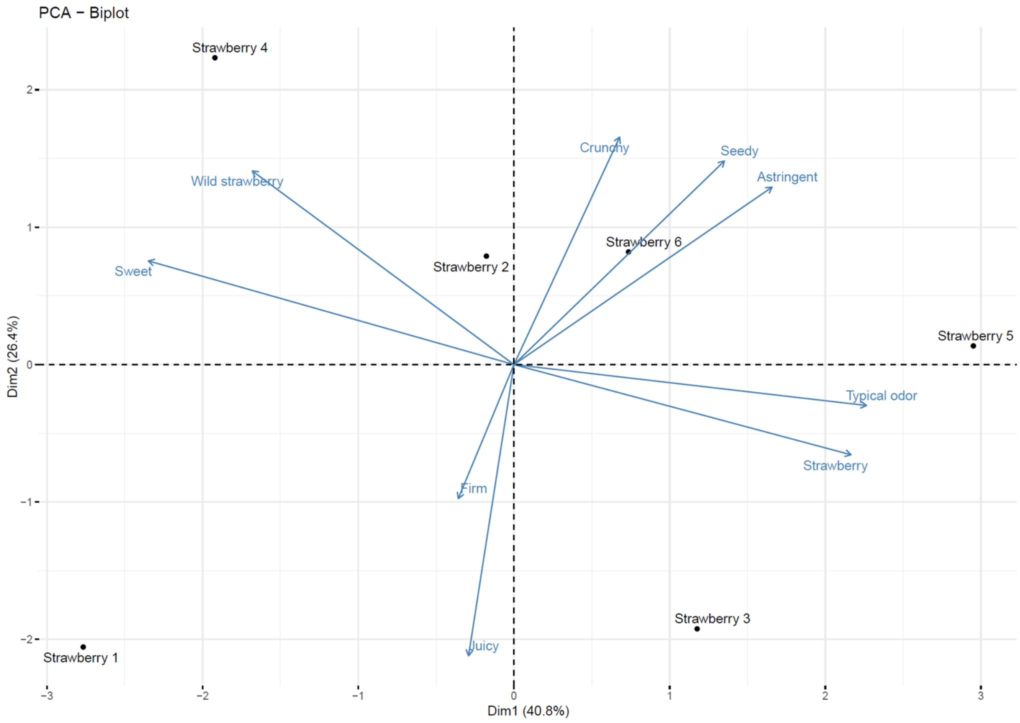



**Figure 4.** Example of principal component analysis (PCA) biplot illustrating the relationships between different strawberry samples and their associated attributes using the RATA method. The plot displays six strawberry samples (strawberry 1 to strawberry 6) and various attributes, such as sweet, firm, juicy, wild strawberry, crunchy, seedy, astringent, and typical odor. The position of each sample in the plot indicates its characteristics based on the two principal components (dim1 and dim2), which explain 40.8% and 26.4% of the variance, respectively. Attributes are represented as vectors, with the length of each vector indicating the importance of the attribute in differentiating between the samples.

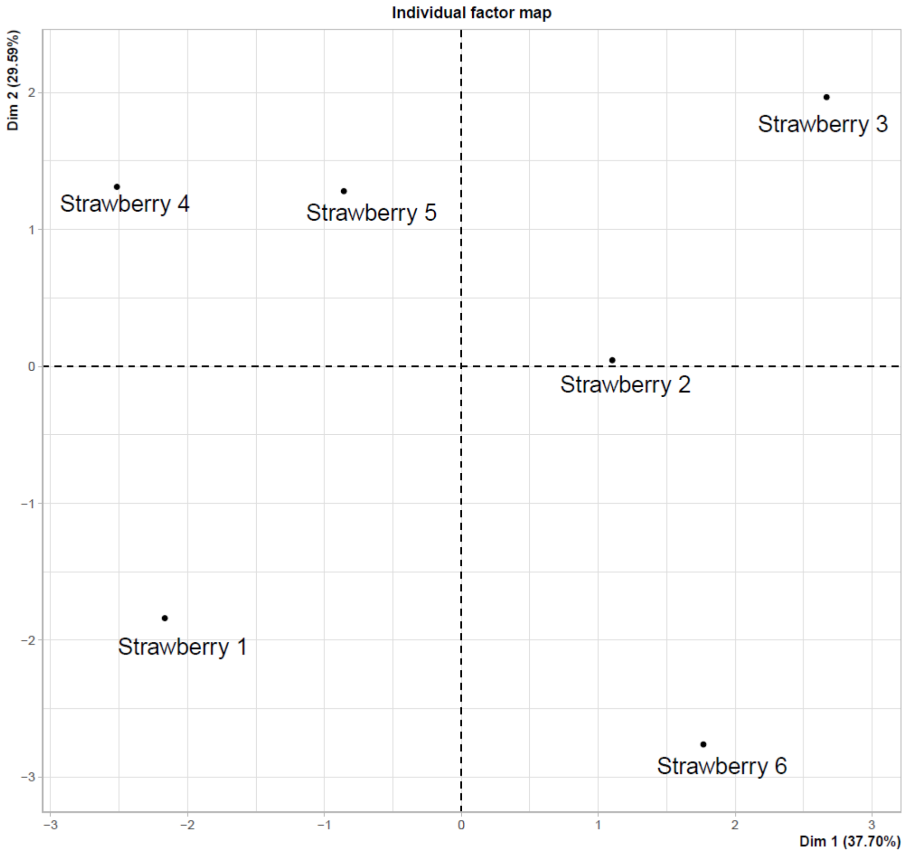
The number of participants needed for the test execution varies according to the aim of the research, ranging from a minimum of 30 to even 200, while considering the samples assessed from 5 to 10 [21,22,39].

The data outcome from the flash profile will be a matrix where the rows represent each individual product evaluated, while the columns represent the consumers, with the attributes listed from the first step of the flash profile and the evaluation values from the second step of the flash profile (Table 2).

**Table 2.** Example of flash profile outcome table (only three attributes and consumers are represented). For each consumer, the attributes defined in the first step are shown together with the ranking value scored in the second step.

| Sample | Consumer 1 | | | Consumer 2 | | | Consumer 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sour | Sweet | Juicy | Sugary | Acid | Succculent | Moist | Crispy | Honeyed |
| Strawberry 1 | 3 | 3 | 1 | 10 | 12 | 6 | 3 | 4 | 5 |
| Strawberry 2 | 2 | 5 | 9 | 16 | 11 | 18 | 7 | 7 | 6 |
| Strawberry 3 | 4 | 5 | 7 | 14 | 10 | 15 | 5 | 9 | 6 |
| Strawberry 4 | 4 | 0 | 1 | 2 | 9 | 6 | 2 | 4 | 2 |
| Strawberry 5 | 8 | 5 | 5 | 11 | 18 | 13 | 6 | 6 | 7 |
| Strawberry 6 | 0 | 8 | 2 | 19 | 2 | 4 | 4 | 5 | 10 |

For data analysis, Multiple Factor Analysis (MFA) can be used (Figure 5a,b) [40].

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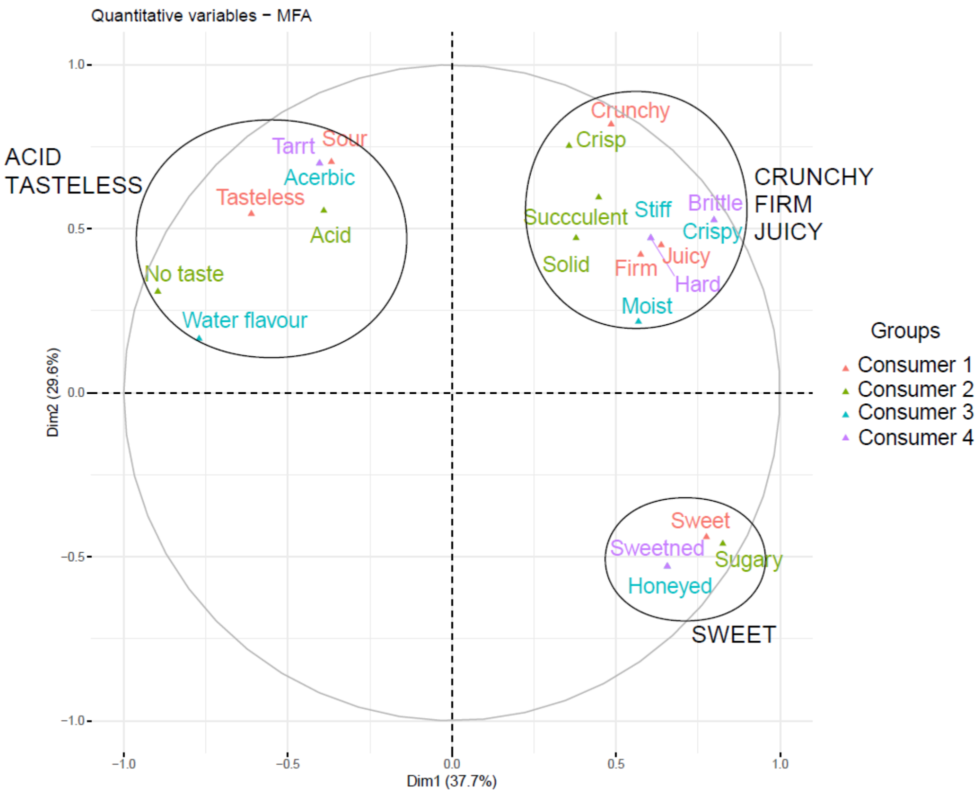



(**b**)

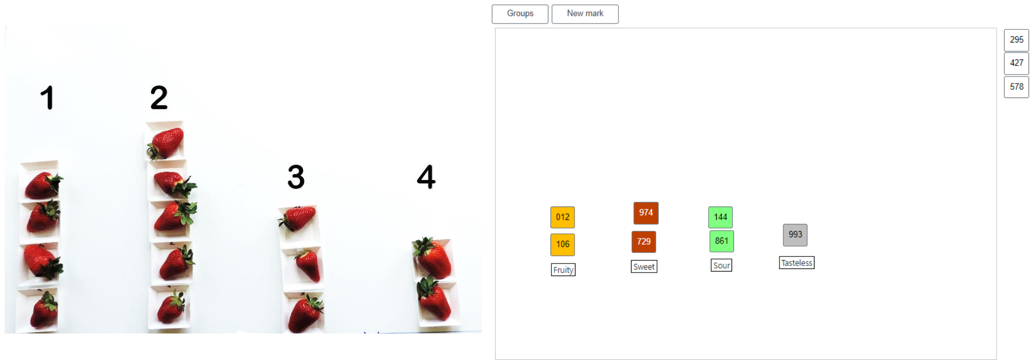
**Figure 5.** Example of MFA describing six different strawberry samples from four consumers. (**a**) Sample maps showing how the products are perceived. (**b**) Attributes map showing the different vocabulary used by each consumer.

The interpretation of similarities and differences among samples in the bidimensional space is usually the most complicated aspect of flash profiling [22,41], as it relies on different consumers identifying the same/similar attributes for describing samples (Figure 5b). FP, like RATA, has the advantage of providing both quantitative and qualitative responses. Thanks to the freedom given to the consumers to use the attributes they previously listed, more spontaneous responses are gathered, and emotional or non-sensory cues for marketing strategies can also be captured. However, the main disadvantage is that the interpretation of the results and the identification of similar attributes from consumers can be complicated and time-consuming.

### *3.2. Holistic Methodologies*

#### 3.2.1. Free Sorting

This is a methodology based on a categorization task, with no attributes involved in the process. Free sorting is a holistic method where subjects are provided with a set of products and are asked to make a sorting task grouping the products among them. The samples belonging to the same group are supposed to be similar but different from those in the other groups (Figure 6a,b). The presentation order of the samples could affect the results, so it is better to randomize the order for each subject to minimize bias [42].




(a) (b)

**Figure 6.** Practical example of free sorting of strawberries. (**a**) Example of sorting tasks with strawberry samples. (**b**) Example of sorting and verbalization task in an electronic device to record the consumer's answers.

The participants are free to sort on the basis of the overall similarities and dissimilarities perceived among the samples, but if the study needs to focus on a particular aim, the test can be addressed to focus on specific traits of the product (i.e., flavor, odor, and texture). The size of the panel varies depending on the nature of the judges used. According to different studies on this method, the size could range between 9 and 389 panelists [39,43,44]. Blancher et al. [45], in a study, suggested working with at least 30 consumers to have stable results.

An advanced version of this method is to couple sorting with a verbalization task, where the panelists, after the product group's formation, have to describe them with their own terms [46]. In this way, the participants provide a list of attributes that characterize the different groups in order to understand which differences and similarities characterize the sorting process. The verbalization step is not easy, especially if the method is processed with consumers, because they are not so familiar with sensory terms [42]. A solution could be to provide the consumers with a list of attributes and let them select all that characterize any single group created. Lelièvre [47] showed that providing a list of terms to untrained assessors compared with free verbalization on beer evaluation provided a larger and more accurate list of terms that better described the same products. On the other hand, a pre-established list provided to the consumers could limit the evaluation by addressing the test only in the direction of the listed attributes with a loss of information derived from the consumer's spontaneous stimuli [42].

The interpretation of the terms provided by consumers in the verbalization task can be one of the main limitations of this method because it could be a time-consuming process, especially if they are untrained. However, a further limitation is that the free sorting task alone does not give the threshold to understand if one product belongs to one group or not. Hence, to solve this problem, some authors asked participants in the verbalization process to indicate for each group formed just the stimulus most representative of each group [48].

The data outcome from the sorting will be a matrix (Table 3) where the rows represent each product evaluated, while the columns represent the consumers with a list of the group formed and the attributes that describe the group.

**Table 3.** Example of a table obtained with six samples and four verbalization attributes provided (fruity, tasteless, sour, and sweet) to three consumers. In the first step, each consumer sorts the samples into groups based on their own criteria (group columns). In the second step, each consumer names each group they formed using the provided attributes (description columns).

| Sample | Consumer 1 | | Consumer 2 | | Consumer 3 | |
|---|---|---|---|---|---|---|
| | Group | Description | Group | Description | Group | Description |
| Strawberry 1 | 1 | Fruity | 2 | Sweet | 2 | Fruity |
| Strawberry 2 | 2 | Tasteless | 2 | Sweet | 1 | Fruity |
| Strawberry 3 | 1 | Fruity | 3 | Sour | 1 | Fruity |
| Strawberry 4 | 2 | Tasteless | 1 | Fruity | 1 | Tasteless |
| Strawberry 5 | 3 | Sour | 1 | Fruity | 3 | Sweet |
| Strawberry 6 | 1 | fruity | 3 | Sour | 1 | Tasteless |

For the data analysis, Multiple Correspondence Analysis (MCA) may be used (Figure 7) [42].

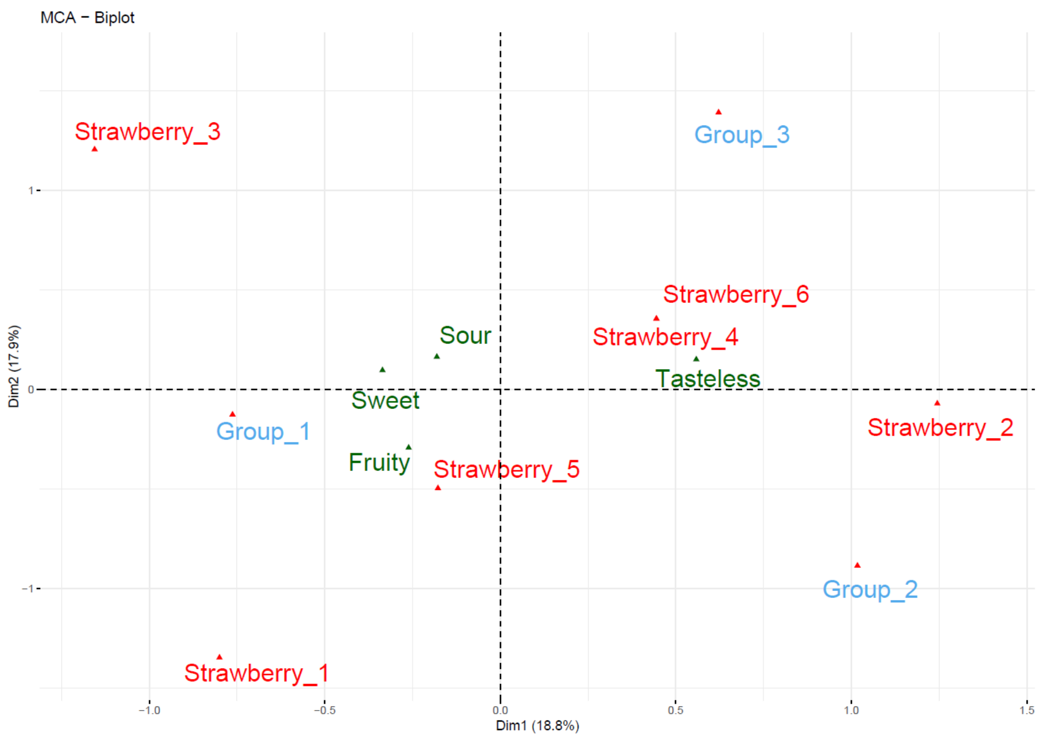
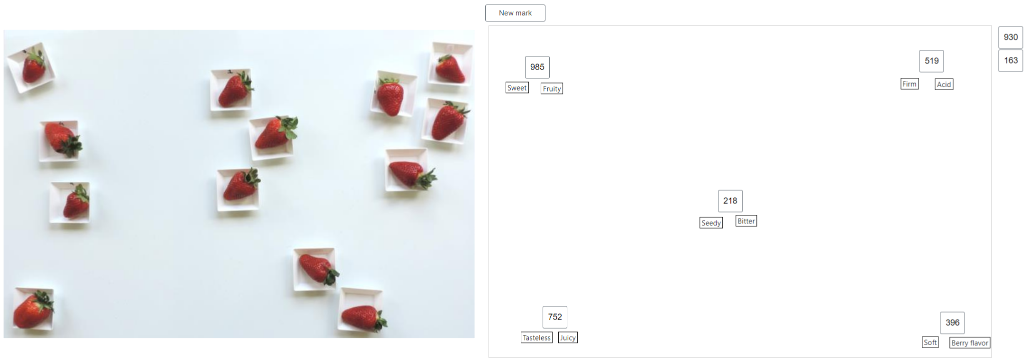



**Figure 7.** Example of MCA describing six different strawberry samples from seven different consumers.

### 3.2.2. Napping and Ultra Flash Profile (UFP)

Napping is a method invented by Jerome Pagés in 2005. The name comes from the French word "nappe" meaning tablecloth, and the first concept of the method is to set the samples on a large piece of paper close or far apart depending on their similarity or differences (Figure 8a,b) [49,50]. Napping could be considered an advancement of projective mapping used in psychology to study the personality of individuals. During a psychological study in 1994, Risvik used projective mapping in a sensory assessment to ask the participants to rank chocolate samples according to their similarities and differences in two distinct rankings [51].




(a) (b)

**Figure 8.** Practical example of napping with strawberries. (**a**) Napping with strawberry samples. (**b**) Napping with ultra flash profile (UFP) in an electronic device to record the answers.

The napping method permits consumers to freely determinate similarities and differences among the samples. A further difference introduced in the method is that the participants have to place the samples in a two-dimensional space instead of a one-dimensional space, capturing more information regarding the consumer's perception of the product.

For a consistent result, at least 50 consumers and fewer than 12 products are suggested [22].

However, the main limitation of napping is that the information on the reason the consumers place the product in the space is not revealed; hence, without being combined with a verbalization task, it remains unknown [52].

To overcome the latent information issue, it is possible to combine napping with the Ultra Flash Profile (UFP) test, where participants are asked after the positioning process to write down in their own words the attributes that best describe any single product evaluated (Figure 8b) [4,53,54].

The data outcome from the napping will be a matrix where the rows represent each individual product evaluated, while the columns represent the consumer product placing coordinates (x,y) and the list of the attributes that describe each product (Table 4).

**Table 4.** Example of a data matrix reporting the outcomes of the napping procedure. The rows represent the samples, while the columns represent each consumer with the coordinates x and y indicating where the samples were placed during the napping phase. Additionally, the attributes (C1) used in the UFP to describe each sample are included.

| **Samples** | **Consumer 1** | | | **Consumer 2** | | | **Consumer 3** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **X1** | **Y1** | **C1** | **X2** | **Y2** | **C2** | **X3** | **Y3** | **C3** |
| straw1 | 40.8 | 54.4 | Sweet; Juicy | 98.1 | 11.8 | Sweet | 97.4 | 34.5 | Acid; Bright |
| straw2 | 39 | 12 | Acid | 90.9 | 10.5 | Acid | 32.3 | 33.8 | Aromatic; Juicy |
| straw3 | 18.5 | 78.3 | Sweet; Tasty | 60.3 | 42.8 | Acid; Bright | 86.3 | 14.7 | Juicy; Sweet |
| straw4 | 27.2 | 21.7 | Tasteless | 78.4 | 35.5 | Acid; Juicy | 69.1 | 17.4 | Sweet; Fresh |
| straw5 | 23.2 | 54.8 | Sweet; Acid | 80.2 | 50.6 | Acid; Crunchy | 31.8 | 11.7 | Sweet; Bright |
| straw6 | 52.6 | 36.6 | Ripe | 47.8 | 46.6 | Sweet; Aromatic | 34.7 | 30.3 | Fresh; Bright |

For data analysis, Multiple Factor Analysis (MFA) may be used for the visualization of pure napping [52,55] (Figure 9).

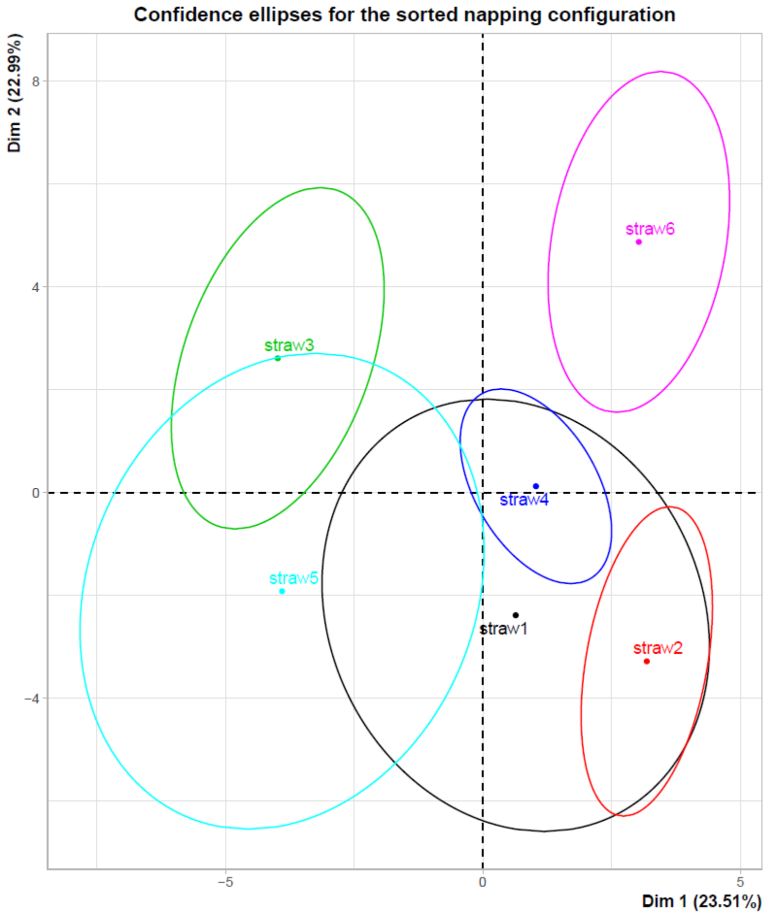



**Figure 9.** Example of MFA performed on the coordinates (x, y) where consumers placed the samples during the napping phase. The MFA illustrates how consumers differentiated the strawberries using napping, with confidence ellipses indicating the variability in sample placement.

For analyzing the verbalization task and understanding how the consumers described the samples, a Correspondence Analysis may be used (Figure 10).

The main advantages of sorting and napping are based on their holistic nature. These methodologies do not require eliciting any terms, thus avoiding bias from predefined attributes. They are easy to perform and are playful tasks, allowing for the collection of spontaneous responses and non-sensory cues. The main disadvantage, however, for both methodologies is that the interpretation of the verbalization task is time-consuming and laborious.

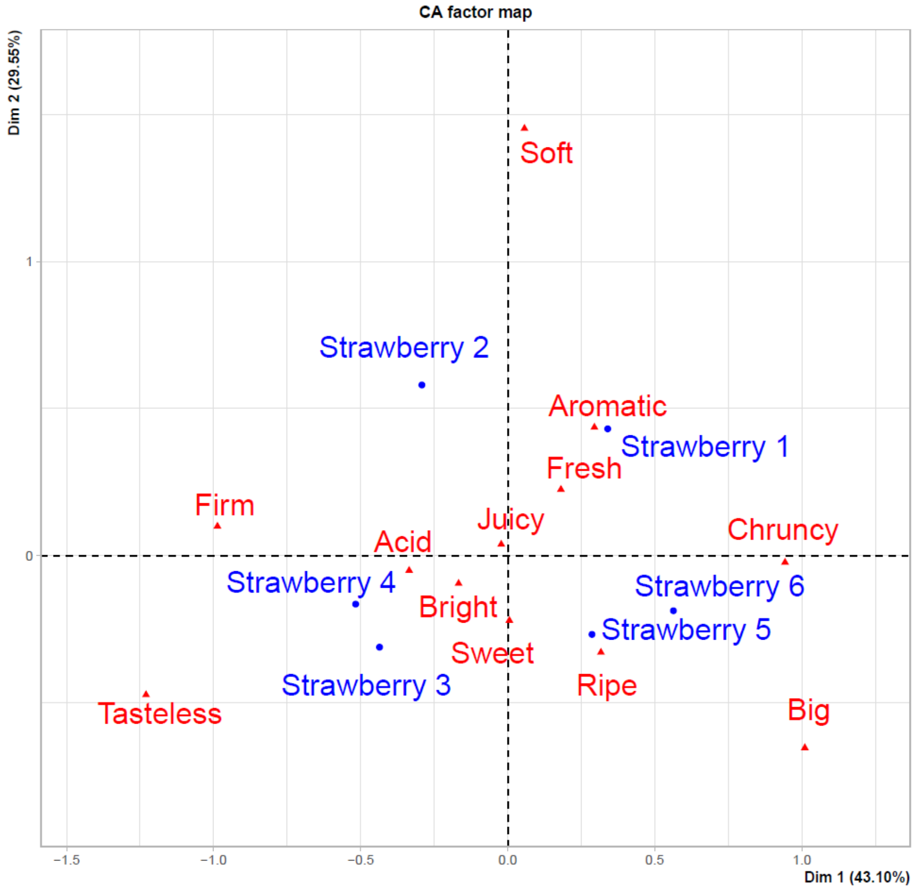



**Figure 10.** Example of CA describing how the consumer describes the strawberry in verbalization after napping.

## 4. Future Prospects with Augmented Reality Integration (AR) and Biometrics

Augmented Reality (AR) is one of the newer ways that humans interact with computers, where virtual content overlaps the real world, creating the illusion of coexisting in the same space [56,57]. Unlike virtual reality, which completely replaces reality with a virtual space, Augmented Reality provides virtual information that interacts with the real world in real time, maintaining perfect alignment [58,59]. For this reason, AR may be better suited for sensory analysis because, unlike virtual reality, it is possible to maintain the real taste of food. The ability of AR to interact with reality offers sensory professionals the possibility to assess how changes in the visual characteristics of a given product (such as color, shape, and size) affect the final consumer perception. Furthermore, it allows sensory professionals to evaluate how this perception is influenced by displaying specific information, such as label details or nutritional content [57].

Integrating AR in sensory methods may also allow the collection of additional information, such as biometric parameters [57]. Biometric data is collected using sophisticated sensors capable of detecting individual physiological or behavioral features. Biometrics are already present in everyday life thanks to the widespread use of technological devices such as smartphones, Fitbits, and other fitness trackers, which integrate sensors capable of detecting personal traits, such as fingerprints or facial recognition, for device unlocking or heart rate monitoring. In sensory analysis, biometrics are applied to detect the body's involuntary or behavioral reactions during a food stimulus, implicitly indicating the individual's emotional state. The autonomic nervous system, which controls involuntary physiological responses, such as heart rate, skin temperature, respiratory patterns, and skin conductivity, is the most commonly studied, and these responses have been investigated in various food products [57,60–62]. Other interesting biometric measures that can be applied include the Facial Action Coding System [63,64], recording eye movements using eye-tracking technology [65], and recording brain wave rhythms using electroencephalography [66]. AR headset technologies may incorporate these biometric parameters, offering a sensory experience that can also capture the involuntary physiological response of consumers. Thus, it is possible to collect new multidimensional data that could compensate for respondents' inability to communicate all the emotions evoked by the sensory experience, enriching the understanding of the emotions driving consumer acceptance of the product [57,63,64].

However, some studies have pointed out limitations that deserve consideration in the future, especially when working with consumers. Indeed, Penco et al. [67], Billinghurst [68], and Rauschnabel et al. [69] have expressed how difficult it is to introduce this new technology to people and make them accept it, even for research purposes. Furthermore, with the widespread use of these technologies, ethical issues may arise, which need more exploration in future research.

## 5. Conclusions

Sensory analysis offers several new methodologies based on consumer input as alternatives to the classic descriptive analysis performed by trained judges. These methods are particularly valuable for those with limited resources in terms of time or funds. This review highlights different methods that can be applied in the strawberry breeding field. CATA [19,28] and napping [53] have already been applied to strawberries in the past. For future prospects, the above-described methods (CATA, RATA, FP, free sorting, and napping) should be integrated into strawberry breeding programs and new cultivars' commercial valorization. Given their nature, holistic tests can be used in the preliminary stages of material selection when the potential of new advanced strawberry selections is not yet clear. In contrast, attribute-based tests may be more suitable for evaluating more promising selections or established cultivars to understand their strengths and weaknesses and how consumers perceive them, combined with the agronomic characteristics that are always fundamental for growers. The high flexibility of these methods and the simplicity of performing the tasks may also allow for the integration of these methodologies with AR technology. This could represent a further step in the science of sensory and consumer research, enabling a complete understanding of real consumer needs while always looking at the ethical issues that cannot be neglected when working with consumers.

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## References

1. FAOSTAT. Available online: https://www.fao.org/faostat/en/#data/QCL (accessed on 18 June 2024).
2. Zacharaki, A.K.; Monaghan, J.M.; Bromley, J.R.; Vickers, L.H. Opportunities and challenges for strawberry cultivation in urban food production systems. *Plants People Planet* **2024**, *6*, 611–621. [CrossRef]
3. Diamanti, J.; Mazzoni, L.; Balducci, F.; Cappelletti, R.; Capocasa, F.; Battino, M.; Dobson, G.; Stewart, D.; Mezzetti, B. Use of Wild Genotypes in Breeding Program Increases Strawberry Fruit Sensorial and Nutritional Quality. *J. Agric. Food Chem.* **2014**, *62*, 3944–3953. [CrossRef] [PubMed]
4. Predieri, S.; Lippi, N.; Daniele, G. What can we learn from consumers' perception of strawberry quality? *Acta Hortic.* **2021**, *1309*, 987–994. [CrossRef]
5. Senger, E.; Osorio, S.; Olbricht, K.; Shaw, P.; Denoyes, B.; Davik, J.; Predieri, S.; Karhu, S.; Raubach, S.; Lippi, N.; et al. Towards smart and sustainable development of modern berry cultivars in Europe. *Plant J.* **2022**, *111*, 1238–1251. [CrossRef] [PubMed]
6. Vicente, E.; Varela, P.; de Saldamando, L.; Ares, G. Evaluation of the sensory characteristics of strawberry cultivars throughout the harvest season using projective mapping: Sensory characteristics of strawberry cultivars. *J. Sci. Food Agric.* **2014**, *94*, 591–599. [CrossRef]

7. Fan, Z.; Hasing, T.; Johnson, T.S.; Garner, D.M.; Schwieterman, M.L.; Barbey, C.R.; Colquhoun, T.A.; Sims, C.A.; Resende, M.F.R.; Whitaker, V.M. Strawberry sweetness and consumer preference are enhanced by specific volatile compounds. *Hortic. Res.* **2021**, *8*, 66. [CrossRef] [PubMed]
8. Folta, K.M.; Klee, H.J. Sensory sacrifices when we mass-produce mass produce. *Hortic. Res.* **2016**, *3*, 16032. [CrossRef] [PubMed]
9. Ulrich, D.; Komes, D.; Olbricht, K.; Hoberg, E. Diversity of aroma patterns in wild and cultivated Fragaria accessions. *Genet. Resour. Crop Evol.* **2007**, *54*, 1185–1196. [CrossRef]
10. Mazzoni, L.; Perez-Lopez, P.; Giampieri, F.; Alvarez-Suarez, J.M.; Gasparrini, M.; Forbes-Hernandez, T.Y.; Quiles, J.L.; Mezzetti, B.; Battino, M. The genetic aspects of berries: From field to health. *J. Sci. Food Agric.* **2016**, *96*, 365–371. [CrossRef]
11. Lado, J.; Moltini, A.I.; Vicente, E.; Rodríguez, G.; Arcia, P.; Rodríguez, M.; López, M.; Billiris, A.; Ares, G. Integration of Sensory Analysis into Plant Breeding: A Review. *Agrociencia Urug.* **2019**, *23*, 101–115. [CrossRef]
12. Hampson, C.; Quamme, H.; Hall, J.; MacDonald, R.; King, M.; Cliff, M. Sensory evaluation as a selection tool in apple breeding. *Euphytica* **2000**, *111*, 79–90. [CrossRef]
13. Brash, D.W.; Charles, C.M.; Wright, S.; Bycroft, B.L. Shelf-life of stored asparagus is strongly related to postharvest respiratory activity. *Postharvest Biol. Technol.* **1995**, *5*, 77–81. [CrossRef]
14. Cetinkaya, N.; Ozyardımci, B.; Denli, E.; Ic, E. Radiation processing as a post-harvest quarantine control for raisins, dried figs and dried apricots. *Radiat. Phys. Chem.* **2006**, *75*, 424–431. [CrossRef]
15. Parvez, S.; Wani, I.A. Postharvest Biology and Technology of Strawberry. In *Postharvest Biology and Technology of Temperate Fruits*; Mir, S., Shah, M., Mir, M., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 331–348. [CrossRef]
16. Garcia, L.C.; Pereira, L.M.; Sarantópoulos, C.I.G.d.L.; Hubinger, M.D. Effect of Antimicrobial Starch Edible Coating on Shelf-Life of Fresh Strawberries. *Packag. Technol. Sci.* **2012**, *25*, 413–425. [CrossRef]
17. Ariza, M.T.; Soria, C.; Medina-Mínguez, J.J.; Martínez-Ferri, E. Incidence of Misshapen Fruits in Strawberry Plants Grown under Tunnels Is Affected by Cultivar, Planting Date, Pollination, and Low Temperatures. *HortScience* **2012**, *47*, 1569–1573. [CrossRef]
18. Cervantes, L.; Martínez-Ferri, E.; Soria, C.; Ariza, M.T. Bioavailability of phenolic compounds in strawberry, raspberry and blueberry: Insights for breeding programs. *Food Biosci.* **2020**, *37*, 100680. [CrossRef]
19. Lado, J.; Vicente, E.; Manzzioni, A.; Ares, G. Application of a check-all-that-apply question for the evaluation of strawberry cultivars from a breeding program: A check-all-that-apply question for the evaluation of strawberry cultivars. *J. Sci. Food Agric.* **2010**, *90*, 2268–2275. [CrossRef] [PubMed]
20. Murray, J.; Delahunty, C.; Baxter, I. Descriptive sensory analysis: Past, present and future. *Food Res. Int.* **2001**, *34*, 461–471. [CrossRef]
21. Delarue, J. The use of rapid sensory methods in R&D and research: An introduction. In *Rapid Sensory Profiling Techniques*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 3–26. [CrossRef]
22. Ares, G.; Varela, P. (Eds.) Chapter 8—Consumer-Based Methodologies for Sensory Characterization. In *Methods in Consumer Research*; Woodhead Publishing Series in Food Science, Technology and Nutrition; Woodhead Publishing: Cambridge, UK, 2018; Volume 1, pp. 187–209. [CrossRef]
23. Ares, G.; Jaeger, S.R. Check-all-that-apply (CATA) questions with consumers in practice: Experimental considerations and impact on outcome. In *Rapid Sensory Profiling Techniques*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 257–280. [CrossRef]
24. Driesener, C.; Romaniuk, J. Comparing Methods of Brand Image Measurement. *Int. J. Mark. Res.* **2006**, *48*, 681–698. [CrossRef]
25. Rasinski, K.A.; Mingay, D.; Bradburn, N.M. Do Respondents Really "Mark All That Apply" on Self-Administered Questions? *Public Opin. Q.* **1994**, *58*, 400. [CrossRef]
26. Smyth, J.D.; Dillman, D.A.; Christian, L.M.; Stern, M.J. Comparing Check-All and Forced-Choice Question Formats in Web Surveys. *Public Opin. Q.* **2006**, *70*, 66–77. [CrossRef]
27. Jaeger, S.R.; Beresford, M.K.; Paisley, A.G.; Antúnez, L.; Vidal, L.; Cadena, R.S.; Giménez, A.; Ares, G. Check-all-that-apply (CATA) questions for sensory product characterization by consumers: Investigations into the number of terms used in CATA questions. *Food Qual. Prefer.* **2015**, *42*, 154–164. [CrossRef]
28. Oliver, P.; Cicerale, S.; Pang, E.; Keast, R. Check-all-that-applies as an alternative for descriptive analysis to establish flavors driving liking in strawberries. *J. Sens. Stud.* **2018**, *33*, e12316. [CrossRef]
29. Meyners, M.; Castura, J.C.; Carr, B.T. Existing and new approaches for the analysis of CATA data. *Food Qual. Prefer.* **2013**, *30*, 309–319. [CrossRef]
30. Bock, T. Improving the Display of Correspondence Analysis Using Moon Plots. *Int. J. Mark. Res.* **2011**, *53*, 307–326. [CrossRef]
31. Ares, G.; Dauber, C.; Fernández, E.; Giménez, A.; Varela, P. Penalty analysis based on CATA questions to identify drivers of liking and directions for product reformulation. *Food Qual. Prefer.* **2014**, *32*, 65–76. [CrossRef]
32. Giménez-Sanchis, A.; Tárrega, A.; Tarancón, P.; Aleza, P.; Besada, C. Check-All-That-Apply Questions including the Ideal Product as a Tool for Selecting Varieties in Breeding Programs. A Case Study with Mandarins. *Agronomy* **2021**, *11*, 2243. [CrossRef]
33. Meyners, M. Testing for differences between impact of attributes in penalty-lift analysis. *Food Qual. Prefer.* **2016**, *47*, 29–33. [CrossRef]
34. Schouteten, J.J.; Gellynck, X.; De Bourdeaudhuij, I.; Sas, B.; Bredie, W.L.; Perez-Cueto, F.J.; De Steur, H. Comparison of response formats and concurrent hedonic measures for optimal use of the EmoSensory® Wheel. *Food Res. Int.* **2017**, *93*, 33–42. [CrossRef]
35. Vidal, L.; Ares, G.; Hedderley, D.I.; Meyners, M.; Jaeger, S.R. Comparison of rate-all-that-apply (RATA) and check-all-that-apply (CATA) questions across seven consumer studies. *Food Qual. Prefer.* **2018**, *67*, 49–58. [CrossRef]

36. Meyners, M.; Jaeger, S.R.; Ares, G. On the analysis of Rate-All-That-Apply (RATA) data. *Food Qual. Prefer.* **2016**, *49*, 1–10. [CrossRef]
37. Lawless, H.T.; Heymann, H. *Sensory Evaluation of Food: Principles and Practices*; Food Science Text Series; Springer: New York, NY, USA, 2010.
38. Dairou, V.; Sieffermann, J. A Comparison of 14 Jams Characterized by Conventional Profile and a Quick Original Method, the Flash Profile. *J. Food Sci.* **2002**, *67*, 826–834. [CrossRef]
39. Varela, P.; Ares, G. Sensory profiling, the blurred line between sensory and consumer science. A review of novel methods for product characterization. *Food Res. Int.* **2012**, *48*, 893–908. [CrossRef]
40. Bredie, W.L.; Liu, J.; Dehlholm, C.; Heymann, H. Flash Profile Method. In *Descriptive Analysis in Sensory Evaluation*; Kemp, S.E., Hort, J., Hollowood, T., Eds.; John Wiley & Sons, Ltd: Chichester, UK, 2018; pp. 513–533. [CrossRef]
41. Albert, A.; Varela, P.; Salvador, A.; Hough, G.; Fiszman, S. Overcoming the issues in the sensory description of hot served food with a complex texture. Application of QDA®, flash profiling and projective mapping using panels with different degrees of training. *Food Qual. Prefer.* **2011**, *22*, 463–473. [CrossRef]
42. Courcoux, P.; Faye, P.; Qannari, E.M. Free sorting as a sensory profiling technique for product development. In *Rapid Sensory Profiling Techniques*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 173–208. [CrossRef]
43. Chollet, S.; Lelièvre, M.; Abdi, H.; Valentin, D. Sort and beer: Everything you wanted to know about the sorting task but did not dare to ask. *Food Qual. Prefer.* **2011**, *22*, 507–520. [CrossRef]
44. Teillet, E.; Schlich, P.; Urbano, C.; Cordelle, S.; Guichard, E. Sensory methodologies and the taste of water. *Food Qual. Prefer.* **2010**, *21*, 967–976. [CrossRef]
45. Blancher, G.; Clavier, B.; Egoroff, C.; Duineveld, K.; Parcon, J. A method to investigate the stability of a sorting map. *Food Qual. Prefer.* **2012**, *23*, 36–43. [CrossRef]
46. Hamilton, L.M.; Lahne, J. Assessment of instructions on panelist cognitive framework and free sorting task results: A case study of cold brew coffee. *Food Qual. Prefer.* **2020**, *83*, 103889. [CrossRef]
47. Lelièvre, M.; Chollet, S.; Abdi, H.; Valentin, D. What is the validity of the sorting task for describing beers? A study using trained and untrained assessors. *Food Qual. Prefer.* **2008**, *19*, 697–703. [CrossRef]
48. Coxon, A.P.M. *Sorting Data: Collection and Analysis*; SAGE: London, UK, 1999.
49. István, M.; Kókai, Z. The applicability of Napping in the analysis of fermented foods and beverages—A review. *Prog. Agric. Eng. Sci.* **2021**, *17*, 119–125. [CrossRef]
50. Pagès, J. Collection and analysis of perceived product inter-distances using multiple factor analysis: Application to the study of 10 white wines from the Loire Valley. *Food Qual. Prefer.* **2005**, *16*, 642–649. [CrossRef]
51. Risvik, E.; McEwan, J.A.; Colwill, J.S.; Rogers, R.; Lyon, D.H. Projective mapping: A tool for sensory analysis and consumer research. *Food Qual. Prefer.* **1994**, *5*, 263–269. [CrossRef]
52. Pagès, J.; Cadoret, M.; Lê, S. The sorted napping: A new holistic approach in sensory evaluation. *J. Sens. Stud.* **2010**, *25*, 637–658. [CrossRef]
53. Oliver, P.; Cicerale, S.; Pang, E.; Keast, R. Comparison of Quantitative Descriptive Analysis to the Napping methodology with and without product training. *J. Sens. Stud.* **2018**, *33*, e12331. [CrossRef]
54. Ruiz-Capillas, C.; Herrero, A.M.; Pintado, T.; Delgado-Pando, G. Sensory Analysis and Consumer Research in New Meat Products Development. *Foods* **2021**, *10*, 429. [CrossRef] [PubMed]
55. Lê, S.; Lê, T.M.; Cadoret, M. Napping and sorted Napping as a sensory profiling technique. In *Rapid Sensory Profiling Techniques*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 219–236. [CrossRef]
56. Ong, S.K.; Nee, A.Y.C. (Eds.) A Brief Introduction of VR and AR Applications in Manufacturing. In *Virtual and Augmented Reality Applications in Manufacturing*; Springer: London, UK, 2004; pp. 1–11. [CrossRef]
57. Crofton, E.; Botinestean, C.; Fenelon, M.; Gallagher, E. Potential applications for virtual and augmented reality technologies in sensory science. *Innov. Food Sci. Emerg. Technol.* **2019**, *56*, 102178. [CrossRef]
58. Azuma, R.; Baillot, Y.; Behringer, R.; Feiner, S.; Julier, S.; MacIntyre, B. Recent advances in augmented reality. *IEEE Comput. Graph. Appl.* **2001**, *21*, 34–47. [CrossRef]
59. Rampolla, J.; Kipper, G. *Augmented Reality: An Emerging Technologies Guide to AR*; Elsevier: Amsterdam, The Netherlands, 2012.
60. Beyts, C.; Chaya, C.; Dehrmann, F.; James, S.; Smart, K.; Hort, J. A comparison of self-reported emotional and implicit responses to aromas in beer. *Food Qual. Prefer.* **2017**, *59*, 68–80. [CrossRef]
61. Verastegui-Tena, L.; van Trijp, H.; Piqueras-Fiszman, B. Heart rate, skin conductance, and explicit responses to juice samples with varying levels of expectation (dis)confirmation. *Food Qual. Prefer.* **2019**, *71*, 320–331. [CrossRef]
62. Torrico, D.D.; Fuentes, S.; Viejo, C.G.; Ashman, H.; Gunaratne, N.M.; Gunaratne, T.M.; Dunshea, F.R. Images and chocolate stimuli affect physiological and affective responses of consumers: A cross-cultural study. *Food Qual. Prefer.* **2018**, *65*, 60–71. [CrossRef]
63. He, W.; Boesveldt, S.; de Graaf, C.; de Wijk, R.A. The relation between continuous and discrete emotional responses to food odors with facial expressions and non-verbal reports. *Food Qual. Prefer.* **2016**, *48*, 130–137. [CrossRef]
64. de Wijk, R.A.; Kooijman, V.; Verhoeven, R.H.; Holthuysen, N.T.; de Graaf, C. Autonomic nervous system responses on and facial expressions to the sight, smell, and taste of liked and disliked foods. *Food Qual. Prefer.* **2012**, *26*, 196–203. [CrossRef]
65. Siegrist, M.; Leins-Hess, R.; Keller, C. Which front-of-pack nutrition label is the most efficient one? The results of an eye-tracker study. *Food Qual. Prefer.* **2015**, *39*, 183–190. [CrossRef]

66. Viemose, I.; Møller, P.; Laugesen, J.L.; Schachtman, T.R.; Manoharan, T.; Christoffersen, G.R. Appetitive long-term taste conditioning enhances human visually evoked EEG responses. *Behav. Brain Res.* **2013**, *253*, 1–8. [CrossRef] [PubMed]
67. Penco, L.; Serravalle, F.; Profumo, G.; Viassone, M. Mobile augmented reality as an internationalization tool in the "Made In Italy" food and beverage industry. *J. Manag. Gov.* **2021**, *25*, 1179–1209. [CrossRef]
68. Billinghurst, M. Grand Challenges for Augmented Reality. *Front. Virtual Real.* **2021**, *2*, 578080. [CrossRef]
69. Rauschnabel, P.A.; Ro, Y.K. Augmented reality smart glasses: An investigation of technology acceptance drivers. *Int. J. Technol. Mark.* **2016**, *11*, 123. [CrossRef]