**UNIVERSITÀ DEGLI STUDI DI TORINO**

**SCUOLA DI DOTTORATO IN SCIENZE**

**DELLA NATURA E TECNOLOGIE INNOVATIVE**

**DOTTORATO IN**

**SCIENZE AGRARIE, FORESTALI ED AGROALIMENTARI**

## CYCLE: XXXIII

# New approaches to evaluate quality of horticultural products


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ANNI

2018; 2019; 2020

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# Abstract

The globalization process followed by the introduction of several players in the internationalized market have increased the competitiveness in the market and forced food operators to differentiate their products to create value to consumers, which have become demanding for products with higher or multiple standards of quality. In this context, the ability of food operators to incorporate tangible drivers of consumption in their products is essential to obtain a sustainable advantage over competitors. Quality, however, has become a very complex concept as the socioeconomic changes in society have created a multidimensional construct of the term, which may assume several meanings over different targets of consumers, food operators and stakeholders. Even when only the eating quality of a product is considered, the quality assessment becomes a multidisciplinary science, where several attributes need to be investigated with a wide spectrum of protocols and statistical techniques. However, for the past twenty years the food supply chain has mainly assessed quality in terms of appearance and eventually too simplistic parameters such as soluble solids or acidity, with the solely goal of ensuring the product's standardization and a sufficient shelf life. This type of assessment is very limited and not effective to predict the consumer's perception of a product attribute or its degree of liking.

New instrumentations such as texturometers or near infra-red sensors (NIR) have been proposed to analyze quality at pre-harvesting and post-harvesting of fruit as they are believed to give better predictions of consumer perception. However, most of them are still lacking in external validation. External validation is a critical point since it increases the risk of having a dissonance between what is measured and what is actually perceived by consumers. Therefore, there is a huge need to improve the

quality assessments protocols with techniques that are more related to consumer perception. Recently, the development of new sensory nd statistical techniques have opened up a new whole world, where it will be possible to perform sensory comparisons that are less time-consuming and to commute data of very different nature in more complex models. These new models are able to handle critical aspects such as nonlinearity, multicollinearity, and account for the critical variability inherent among assessors and sample's replicates. They are also employable to assess quality at a pre-harvesting stage, since this type of assessment shares the same kind of problems. However, their interpretation is challenging as they are multi-structured and more complex. Therefore, the aim of the PhD program was to develop new protocols to perform quality assessments to investigate the relation among analytical parameters, sensory attributes and liking of products. Considering the industrial nature of this PhD program, which was born from the agreement between the company Sata SRL and the research department DISAFA under an apprenticeship of higher education cannot, all quality assessments were performed under the context of applied marketing strategies to promote the quality of horticultural products. More specifically, the strategies of branding, taste segmentation through the promotion of single-cultivar's products and the introduction of new club varieties were the contexts used to develop a tailored quality assessment, designed to deal with the critical aspects that arises from each marketing strategy. All quality assessments shared a common structure that involved the development and improvement of protocols under 3 main aspects: analytical, sensory and statistical. While the analytical step involved the improvement of new instrumentation's protocols such as colorimeter and texturometers, the sensory step involved the application of new sensory methods to characterize products, using trained, semi trained and consumer assessors. The statistical step has foreseen the use of complex models that are able to commute data of different sources, obtained by the previous steps.

In this research it can be concluded that, despite the marketing context or the fruit crop, the combination of analytical indexes might be a solution to represent sensory attributes that are multicomponent, such as colour and texture, especially if indexes are created with suitable statistical models such as the Multiple Factor analysis and the Partial least square model, which are able to balance the weight of single parameters to obtain a global representation of an attribute and to investigate its relation with liking. Moreover, the use of more complex models is also suitable to deal with many critical aspects, such as the variability of fresh produce or the uncertainty linked with the human judgment when sensory data need to be collected. This work also confirms how new sensory methods, such as Check-all-that-apply, Penalty analysis and Projective mapping, are suitable to characterize products, regardless the level of training of assessors. We also presented new statistical approaches, either to validate attributes to be part of the sensory questionnaires, either to interpret the results, limiting arbitrariness that is commonly present in this type of assessment. However, we do recognize that small data was a limit in this research and we hope that future research might apply the approaches and the codes shared in this thesis to further validate our new methods.

# 1- Introduction

## 1.1- The purpose of a higher education and research apprenticeship

The globalization process dictated by standardization, deregulation and the use of new technologies has led to the introduction of several players in the internationalized market, which has increased the competitiveness among food operators also in the horticultural sector. The current situation forces warehouses and industries to develop different strategies to differentiate their products in order to create and deliver value to consumers, which are surrounded by countless options in the market and have become more demanding for products with higher standards of quality. Within this context, the ability of food operators to identify and incorporate tangible drivers of consumption in their products is essential to increase the perceived quality and customer satisfaction, and to obtain a sustainable advantage over competitors (Zaynutdinova et al., 2017).

Quality, however, has become a very complex concept in the past twenty years as the socioeconomic and cultural changes in society have created a multidimensional construct of the term, which may assume several meanings over different targets of consumers, food operators and stakeholders as they have different perspectives throughout the food chain (Schreiner et al., 2013). As a consequence, the quality assessment has become a multidisciplinary science, where several attributes need to be investigated with a wide spectrum of protocols and statistical techniques. In the present highly inter-connected food chain, the final client is assumed to be the final customer and food operators are claimed to play a dual role in which they demand or are subjected to different commercial requirements, whether they act as suppliers or clients at each step of the supply chain. In this context, a shared and deep understanding of the diverse quality perspectives is key to build solid collaborations in order to increase the quality of products, and hence, the customer satisfaction. Therefore, only food operators with a multidisciplinary approach that integrates knowledge and skills to find a wide range of solutions for each step of the food chain will succeed and take over the market.

In this context, Sata SRL, a company located in Quargnento (AL) that offers integrated services of consultancy and analytical controls for the agri-food supply chain, and the DISAFA department in the role of a scientific institution, have decided to invest their resources on a higher education and research apprenticeship project in order to develop and add value to different analytical services proposed to food operators that seek to have a broader and deeper understanding of their product's quality. The goal of the project was to develop new techniques to evaluate the quality of fruit products using a multidisciplinary approach that integrates:

- the use of novel instruments;
- the application of new analytical and statistical protocols used in other fields;
- the development of new indexes and appropriate quality assessment's methodologies to be applied at different stages of the agri-food supply chain (pre-harvest, postharvest and processed products).

Considering the importance of including techniques that are more related to the consumer experience, the project has also foreseen the sensory training of a part of the internal staff of Sata srl in order to broaden the quality assessment and apply newly introduced protocols of this area.

A key-element of the project was the integration between the knowledge and the scientific methodologies that are disseminated and mastered in the research field by the DISAFA's department, with the multiple inputs and ideas originated from the careful reading of agricultural sector's needs and problems introduced by Sata SRL. This has led to the creation of innovative solutions to the food chain where service companies and universities may represent a trustful partner to read and solve problems of actors that operate at different steps of the agri-food chain.

## 1.2- The evolution of the quality concept and the interaction with new valorization strategies in the agri-food sector

Quality has been often described as a combination of intrinsic and extrinsic features (Kyriacou et al., 2018), where the intrinsic features regard the physicochemical properties that are inherent to the nature of the product and are strongly influenced by genotype, environmental conditions and agronomic techniques (Gatti et al., 2009), while the extrinsic features regard mostly the consumer preference and expectations, which are highly impacted by cultural, socioeconomic and marketing factors at different degrees (Kyriacou et al., 2018). Recently, marketing researches have shown that consumer's preferences are much more affected by lifestyle and fashion trends than economic factors such as income and education (Schreiner et al., 2013). Considering lifestyle changes over the course of a costumer's life, consumer preference and quality requirements are permanently evolving. Therefore, both intrinsic and extrinsic factors are constantly interacting rather than being separate and complementary to each other. Fashion trends and companies' marketing strategies, for instance, repeatedly affect consumer preference to create new food trends and quality standards, which will then result in the formulation of new intrinsic requirements requested by retailers and industries.

In the agricultural sector, food trends are composed by different product's features that can be distinguished between search, experiential and credence attributes based on the type of quality that can be assessed by the consumer at different stages (Moser et al., 2011). Search and experientials features are tangible characteristics that can be assessed before (visually) or after consumption, such as price, dimension, size and colour in the first case and texture, taste, aroma, and ease of consumption in the second one. Credence features, instead, are intangible outcomes related to environmental conservation, origin, supporting small-scale agriculture and local rural communities, farmers living or producing conditions and workers' rights (Moser et al., 2011). At the present, the sector has identified as most influential a mixture of different types of food trends, such as: convenience, functional foods, organic, food flavour and regional food (Schreiner et al., 2013; Vukasovič et al., 2016), which are in turn a result of a partially contradictory demand for healthy, novel, reliable, and sustainable products with higher standards of experiential eating quality in terms of convenience and flavour. It is well known that the demand for credence features has increased in the last years (Moser et al., 2011), especially among young adults such as the so-called "Y" or "millennials" (Molinillo et al., 2020) and the "Z" generations (Su et al., 2019). However, the eating quality remains a pillar of the quality concept as it is the baseline for consumer acceptance of food before a costumer formulates an idea of preference, and therefore it is vital for the successfulness of a product, even though it is not possible to find a uniform and static flavour preference among consumers during the course of their lives. Confirming this, it has been shown in studies relative to the horticultural sector that when price varies within a precise range, purchase decisions are mostly based on the perceived and experiential quality (Harker et al., 2003).

With respect to the abovementioned food trends, whether they are based on credential or experiential features, vegetables and fruits are very fashionable due to their proved benefits to health (Baselice et al., 2017), the intense development of commercial and agronomic strategies that are more environmentally friendly (Vukasovič et al., 2016) and the possibility to please different targets of consumers due to the widespread availability of different quality profiles among vegetable and fruit crops. This awareness has led to the transfer of many of the existing marketing strategies in the industrial segment to the horticultural sector in order to communicate credentials and experientials values intrinsic to a vegetable product. Some examples are: the development of premium and private label brands, the development of traditional single-variety processed products for taste segmentation and local proposition, and the intense research to introduce novelty and "premiumness" by means of new crops or club varieties in the market. All of these marketing strategies are valuable examples of how the sector is valorizing horticultural products by promoting recognition and reliability (through branding), differentiation and a sustainable consumption of products (through processing followed by the creation of different versions of a product), and finally innovation, but also creation and protection of the value of new cultivars (especially with the introduction of club varieties). Inevitably, all those factors will have an impact on consumers and stakeholders' expectations. For example, in the context of a Brand, of which goal is to boost the notoriety of a product and promote recurrent purchases throughout the season of a product (Zaynutdinova et al., 2017), the length of the season and the homogeneity of quality will unequivocally determine the success of a given product.

However, when applying consolidated marketing strategies coming from the industrial field, food operators must take into account differences between fresh and industrial products on the quality management to assure consumers and stakeholders quality requirements are fulfilled. Unlike processed food, fresh vegetables present many critical aspects to be handled: they are perishable, they have a high within batch variability and their quality may vary greatly throughout the commercial season and over the years depending on the crop or different external factors such as pre-harvest conditions (environmental conditions, agronomic techniques, time of harvesting) or postharvest conditions (warehouse and retail management). Nonetheless, special attention must be dedicated to the quality assessment methodology, which will require the development of protocols and statistical techniques that are robust to deal with critical aspects involving fresh produce, such as the difficulty of comparing varieties that are sequentially harvested; and effective to detect and display differences among products despite the inner variability linked to the batch, considering product differentiation in brands will become more and more important in the future (Harker et al., 2003).

## 1.3- The current quality assessment methodologies: the overview of a multidimensional discipline

To fulfill the requirements of different consumer's segments, the various consumer preferences first have to be identified, especially those concerning the perceived taste considering its primary role in food acceptance. However, in order to match different targets of consumers, it is equally important to identify a corresponding quality profile of the product itself and hence assess its quality attributes (Schreiner et al., 2013). Moreover, the estimation and quantification of key quality attributes is important as it enables food operators to monitor the quality of products throughout the supply chain (Kyriacou et al., 2018) and verify its standardization. Therefore, at the research level, there has always been an intense development of new quality protocols for vegetables and fruit's quality to help food operators to fulfill these goals.

Because there is available a huge amount of quality protocols to be chosen, at the research level an important issue concerning fruit and vegetable quality assessments has become the choice of parameters, instruments and statistical models to investigate product's quality either in global terms, when several parameters need to be integrated to formulate a global judgment of a complex quality attribute (e.g. texture or freshness), either from a specific point of view, when a specific parameter is potentially a strong indicator of a quality attribute (e.g. total soluble solids and sweetness perception). However, when considering the industrial sector, the quality assessment is still conducted using only conventional parameters such as the total soluble solids (TSS), the titrated acidity (TA) and the firmness measured with a penetrometer to monitor the quality throughout the supply chain or to validate new products and brands, as the limits of some of these parameters have also been established by regulation for determinate crops (e.g. the Commission Implementing Regulation (EU), 2011 concerning citrus fruits or the UNECE standard concerning melons) or are important for logistic purposes (e.g. firmness for kiwifruits). Along with them, several visual parameters are assessed as they are imposed by European regulation with the solely goal of performing an easy quality assessment to ensure product's standardization and an acceptable shelf life. Unfortunately, this type of assessment is very limited and there is still a huge lack of correlation between the current industrial approach and the consumer perception of a product attribute or its degree of liking, as it was demonstrated by numerous works (Kyriacou et al., 2018). In fact, currently this type of assessment is merely ensuring an ideal of acceptance linked to the appearance of products, which is expressed in terms of absence of defects concerning external and internal parts of fruits, colour and shape development, regardless their taste. As a result, over the past twenty years the appearance of products has mostly determined their commercialization value and breeding companies have dedicated most of their resources on an intense research for varieties that are more appealing to the eyes at expense of varieties that are more appealing to the taste (Rocha et al., 2013). This has obviously increased the level of dissatisfaction among consumers, whose recurrent purchase is mainly based on taste and flavour perception (Magwasa et al., 2015). Therefore, there is still an urgent need to improve the current quality assessment applied at the industrial level. Nonetheless, the huge gap between what has been developed and proposed at the research level and what is actually used at the industrial level is also an issue to be investigated in order to enhance the transfer of knowhow and technology among the two parts.

At the research level, many are the attempts to develop protocols using new instrumentations that are believed to give better predictions of consumer perception and are less time-consuming than conventional methods once the instruments are calibrated. These new methods usually involve the use of more complex instruments such as texture analyzers, near infra-red sensors (NIR) sensors and electronic noses (Benedetti et al., 2009; Chen et al., 2013a) to investigate different aspects of eating quality attributes, such as texture, taste, and aroma, respectively, and individuate specific parameters that are more related with consumer perception of food. Moreover, since it is assumed that fruit composition at harvest is a reliable descriptor of postharvest quality (Nordey et al., 2019), there is an attempt also to use some of those instruments at the pre-harvest phase, like specific NIR sensors such as the DA-meter® (University of Bologna patent M02005A000211) or the Kiwi-meters® (University of Bologna patent PD2009A000081) (Costa et al., 2009). Even though those instruments rely on very different mechanisms, a common feature shared among them is the enhanced sensitivity to capture and quantify specific molecules or physical phenomena that are very correlated to food perception, for example, the ability to quantify different groups of molecules that contributes to the sweetness or fruity aroma perception, in the case of NIR or the electronic nose, or the ability of a texture analyzer to measure the extent of different physical phenomenon in terms of time, deformation and changes in force that occur in food during a compression test.

However, despite many protocols have been proposed for these instruments, there is a great variability among them concerning the instrument setting, and most are still lacking in external validation, other than being expensive, time-consuming to perform calibrations and of difficult interpretation in order to be adopted by industries and warehouses (Benedetti et al. 2009; Chen et al., 2013a). The lack of an external validation is a huge issue as it increases the risk of having a dissonance between what is measured and what is actually perceived by consumers. While many efforts have been made to individuate factors that affect quality of vegetable and fruit products, there is a limited understanding on how variations of quality attributes may affect consumer perception and how each attribute affect the perception and overall liking of a product across different horticultural crops (Kyriacou et al., 2018). This phenomenon is even more felt for products that are described by multicomponent attributes, which are a result of the interaction of specific parameters. For example, the global attribute texture involves specific but complex parameters such as crispness and juiciness, that can be described by a set of phenomena of different nature, such as sound and hardness to describe an apple’s crispiness or the amount of water and the velocity of water release to describe apricot’s juiciness. This is why the use of sensory methods is still the most advantageous way to assess consumer perception. The ability of integrating different aspects of an attribute to formulate a global judgment (Contador et al., 2015) is a key component of a quality assessment that is not easily replaced by laboratory instrumentation. Therefore, despite all efforts to develop instrumental protocols and the well-known drawbacks linked to conventional sensory tests such as length of training period in the case of panel tests or the variability of responses among individuals in the case of consumer tests, the sensory methods are still the most reliable way to predict consumer perception of food.

Sensory methods are widespread among industrialized food companies, who routinely use profiling techniques to define and quantify the sensory characteristics as this information has numerous applications such as product development and improvement, quality control, advertising claim substantiation as well as understanding both consumer preferences and their relationships with instrumental data (Valentin et al., 2012). However, in the agricultural sector, such methods are scarcely employed, even at the more technically and scientifically developed institutions, such as breeding companies, where yield, product firmness, shelf life and pest tolerance, combining ambient adaptation and agronomic management were prioritized at the expense of vegetable's sensory traits. Probably, this is due to the fact that conventional descriptive analysis, such as Quantitative Descriptive Analysis (QDA), are time and resource consuming, which limits its application in many breeding programs and among warehouses (Lado et al., 2019).

Luckily, in the last few years, the development of new sensory protocols and the introduction of new statistical models have opened up a new whole world to the research and industrial field, where it will be possible to perform sensory protocols that are less time-consuming than the conventional methods as they do not require a training phase and are more effective as they usually rely on our better ability to compare products rather than evaluate them on an absolute scale; and to use statistical models that commute data of very different nature, such as those of analytical, sensory and consumer tests (Valentin et al., 2012). With these new methods, we believe the goal of performing a complex multidisciplinary quality assessment can be achieved and protocols utilization can be finally extended to the food supply chain. Even though a major effort will be needed to interpret new statistical models that are multi-structured and complex, researches and industrials will benefit from their property of handling nonlinear patterns and collinearity that might exist among analytical measurements or between analytical measurements and sensory data, and account for the variability originated by critical factors intrinsic to this type of study, such as the inherent variability among assessors and sample's replicates. Moreover, multi-structured models are also employable to assess quality at a pre-harvesting stage to adjust or improve the decision making related to harvest dates and product commercialization, since this type of assessment shares the same kind of problems described above.

## 2- The Ph.D programme proposition under the apprenticeship of higher education and research

Over the last 15 years, Sata srl has engaged several partnerships with different professionals in the agri-food area to become, from an agronomic studio, a limited liability company that meets the increasingly complex needs of food operators with services that integrates consultancy and analysis designed for different steps of the supply chain. After more than 20 years performing quality assessments at retail platforms and limitedly in laboratory, the company felt the need to improve the current methodology to respond to other food operator's requirements and contribute to disseminate the application of more reliable approaches that take into account the consumer perception to investigate the quality of products. To achieve this purpose, Sata srl and the DISAFA's department have decided to invest their resources on an employee with a technical profile projected towards the food technology and sensory science in order to carry out the research program on new approaches to evaluate quality of horticultural products. The main goal of the project was to develop quality assessment's methods that provide to the sector a better understanding of how variations of quality attributes affect harvesting or post harvesting quality, attribute's perception and overall liking of different fruit crops.

The project was structured in the following steps:

1. Study and development of new analytical protocols and indices with instruments that are commonly employed in the research field but of little use in the business world;
2. Study and application of new methodologies recently introduced in the sensory science. This part was preceded by a theoretical and practical sensory training of part of the internal staff of Sata srl and most of the sensory data used in the project came from the Sata SRL's panel.
3. Study and application of statistical tools to handle data issues concerning horticultural products assessments;

Considering that a PhD program under an apprenticeship of higher education cannot disregard the current business strategies that interact with and impact the theme of its research, in this project, all quality assessments were contextualized under recurring marketing strategies to promote and communicate the quality of horticultural products. More specifically, the following strategies in table 1 were chosen as the marketing context for the quality assessment trials.

This means that the concepts of quality concerning each type of marketing strategy were identified, and each step of the research program was designed in order to handle the critical aspects derived from each marketing strategy.

| | **Branding** | **Taste segmentation** | **Introduction of club varieties** |
|---|---|---|---|
| **Marketing strategy** | To promote the recognition of a product and its proposed quality to obtain a recurrent purchase over time | to create different versions of a product as consumers are less resistant to higher prices compared to the standard version of the same product | To introduce novelty in the market and to allow creation and protection of the value of new cultivars |
| **Quality management strategy** | To assure quality and homogeneity of fruit throughout the commercial season | To identify quality attributes that are easily distinguishable by consumers among product's versions | To identify pre pre-harvest indices that assure product's best postharvest quality |
| **Design of quality assessment** | Longitudinal study of postharvest quality | Vertical study of quality (comparison | Longitudinal study of pre-harvest quality |

| | | | |
|---|---|---|---|
| | | among samples at 1 time-point) | |
| **Products tested** | -Apricots<br>-Strawberries<br>-Honeydew melon<br>-Orange pigmented cultivars "tarocco" | Apple juices<br>Kiwi-berries (*Actinidia arguta*)<br>Apples<br>Bananas<br>Avocado | Kiwi-berries (*Actinidia arguta*) |

Table 1. The marketing and quality management strategies chosen to build the quality assessments developed during the three years of the project.

All quality assessments shared a common structure, with content variations based on the goal of the marketing strategy:

| | **Branding** | **Taste segmentation** | **Introduction of club varieties** |
|---|---|---|---|
| **Quality assessment steps** | *Parameters, protocols and statistical analysis included* | | |
| **1-Physicochemical characterization** | -TSS<br>-TA<br>-Firmness or Texture with the analyzer<br>-Colour | -TSS<br>-TA<br>Firmness or Texture with the texture analyzer<br>-Colour | -TSS<br>-TA<br>-Firmness or Texture with the texture analyzer<br>-Colour<br>-Nutraceutical compounds |
| **2- Sensory characterization** | -Panel test (conventional methods with | -Panel test<br>-Consumer test (new methods: | - |

| | | | |
|---|---|---|---|
| | quantitative scales) | Projective mapping and Check all that apply questionnaire (CATA) | |
| **3-Univariate analysis** (differences among samples for each physicochemical parameter or sensory attribute) | -Physicochemical data: One-factor Analysis of variance (ANOVA)<br>-Sensory data: ANOVA mixed model | -Physicochemical data: One-factor Analysis of variance (ANOVA)<br>-Sensory data: ANOVA mixed model, Chi-squared test, McNemar test | -Physicochemical data: One-factor Analysis of variance (ANOVA) |
| **4-Multivariate analysis** (global analysis of relationships between parameters and between samples) | -Multiple factor analysis | -Multiple Factor analysis<br>-Multiple factor analysis for contingency table | -Multiple factor analysis |
| **5-Regression analysis** (identification of main attributes to predict overall liking or harvesting quality) | -Fuzzy model<br>-Partial least squares model | -Nonlinear partial least squares model | -Partial least squares model |

Table 2 Parameters, protocols and statistical analysis included for each quality assessment steps

By assessing the table 2, in the univariate step it is possible to notice that for sensory methods the number of statistical approaches is higher than the number of statistical approaches used for the physicochemical data.

# 3- The activities carried out:

## 3.1- Study and development of new analytical protocols and indices with instruments that are commonly employed in the research field but of little use in the business world

Alongside with the use of conventional methods to determine TSS and TA values, we have focused on the creation of protocols and indices using the instruments TA.XT2+ texturometer (Stable Micro Systems, Surrey, U.K.) and the CR-400 colorimeter (Konica Minolta, Tokyo, Japan). Both instruments and related software are designed to perform advanced analysis of texture and colour by providing additionally synchronized data measurement alongside the traditional analysis data (e.g. gumminess other than firmness in the case of the texture analyzer) and a higher flexibility when programming the instrument to perform a protocol as they allow the customization of library tests. This means that users are allowed to measure a wider range of more specific parameters compared to the commonly used instruments by food operators such as penetrometers, which are only able to measure the firmness of a product, and colour charts, which do not allow to split colour in its several attributes, such as qualitative traits, as taint, or quantitative traits, as luminosity or saturation (Pathare et al., 2013).

It is important to note that, although both instruments are already commonly used in the research field, a shared methodology with validated indices are still lacking due to the great variability of protocols that were proposed for the same type of product; and the lack of information concerning how the instrument should be set to perform the analysis is still a huge problem since many articles have been omitting this information (Chen et al., 2013b). More specifically, considering the texture analysis of horticultural products, few attentions have been paid to the preparation of samples in terms of shape and specimen, and there is often a huge confusion regards the choice of which parameters should be taken into account for each specific horticultural crop as in the case of the texture analysis profile (TPA), where the instrument is set to give the full range of parameters regardless the type of fruit (Nishinari et al., 2018).

Therefore, the new protocols were developed taking into account the abovementioned sources of variability, and were further enriched with composite indicators by integrating the parameters obtained by the instruments in new formulas when the parameter itself was considered to be poor to predict the wanted attribute (e.g. composite colorimetric indices to investigate the stage of maturity) (table 1).

| | |
|---|---|
| Chroma | $\sqrt{a^2 * + b^2 *}$ (Pathare et al., 2013) |
| Hue angle | $tan^{-1}\frac{b*}{a*}$ (Pathare et al., 2013) |
| CI | $1000 \times a */L * \times b *$ (Pathare et al., 2013) |
| MIC | $L * \times a */b *$ (Manera et al., 2013) |
| COL | $2000 \times a */(L * \times C *)$ (Pathare et al., 2013) |
| H index: | $(180 - h)/(L * + C *)$ (Cristina et al., 2014) |

Table 3. Example of composite colorimetric indices already tested in literature that were used in the quality assessments.

Also, in the case of the texture analyzer, we have developed new scripts on the instrument's software to assess indexes that were not yet present in the current software, such as crispness (Fig. 1) and variants of the default measurement of hardness (Fig 2 and 3).

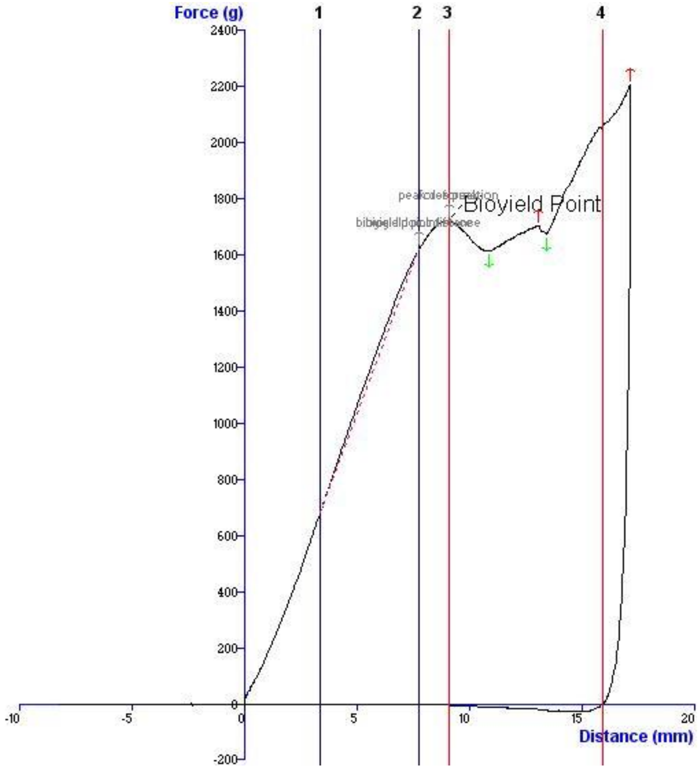


Fig. 1 Example of a force-distance curve obtained by the modified compression test's script. The number of positive (green) and negative (red) peaks and the average drop were automatically calculated between the 3rd and 4th anchors (anchors in red) in order to estimate the crispness of products.

```
 1:        Clear Graph Results
 2: Change Y Axis Type Force
 3: Change X Axis Type Time
 4: Change Units Force g
 5: Change Units Time sec
 6: Change Units Distance mm (Relative)
 7: Go to Max. Time
 8: Search Backwards
 9: Go to Peak +ve Value Force          ( ! ? )
10: Mark Value( Force (Current Units) )         ( R )
11: Go to Peak +ve Value Force          ( ! ? )
12: Hardness = Mark Value( Force (Current Units) ) As Hardness ( R g )
13: Go to Peak +ve Value Force          ( F ? )
14: IF NOT FAIL
15:     Fracture force = Mark Value( Force (Current Units) ) As Fracture force  ( R )
16:     Fracture distance = Mark Value( Distance (Current Units) ) As Fracture distance ( R )
17: END IF
18: Go to Min. Time
19: Search Forwards
20: Drop Anchor
21: Go to Peak +ve Value Distance     ( ! )
22: Drop Anchor
23: Go to Force 0 g
24: Drop Anchor

25: Go to Peak +ve Value Distance     ( ! )
26: Search Backwards
27: Go to last Force
28: Drop Anchor
29: Search Forwards
30: Go to Peak +ve Value Distance
31: Drop Anchor
32: Go to last Force
33: Drop Anchor
34: Go to Min. Time
35: Search Forwards
36: Inflexion (Increasing) 5 ( ! )
37: Drop Anchor
38: Inflexion (Decreasing) 5 ( ! )
39: Drop Anchor
40: Mark Value( Force (Current Units) ) As bioyield point       ( R )
41: Mark Value( Distance (Current Units) ) As bioyieldpoint     ( R )
42: Select Anchor 2 Anchor Not Activated      ( F ! )
43: Select Anchor 1 Anchor Not Activated      ( F ! )
44: Area( Active vs Active )  ( R )
45: Time Difference(  )       ( R )
46: Select Anchor 3 Anchor Not Activated      ( F ! )
47: Area( Active vs Active )  ( R )
48: Select Anchor 2 Anchor Not Activated      ( F ! )
```

Fig. 2 The script created by altering the texture analyzer's software original script for the Texture Profile Analysis (TPA) test. From lines 36 to 42, news instructions were introduced to measure the parameter Young's module. The parameter is claimed to be a reliable indicator of hardness, as indicated in Chen et al. (2013b).

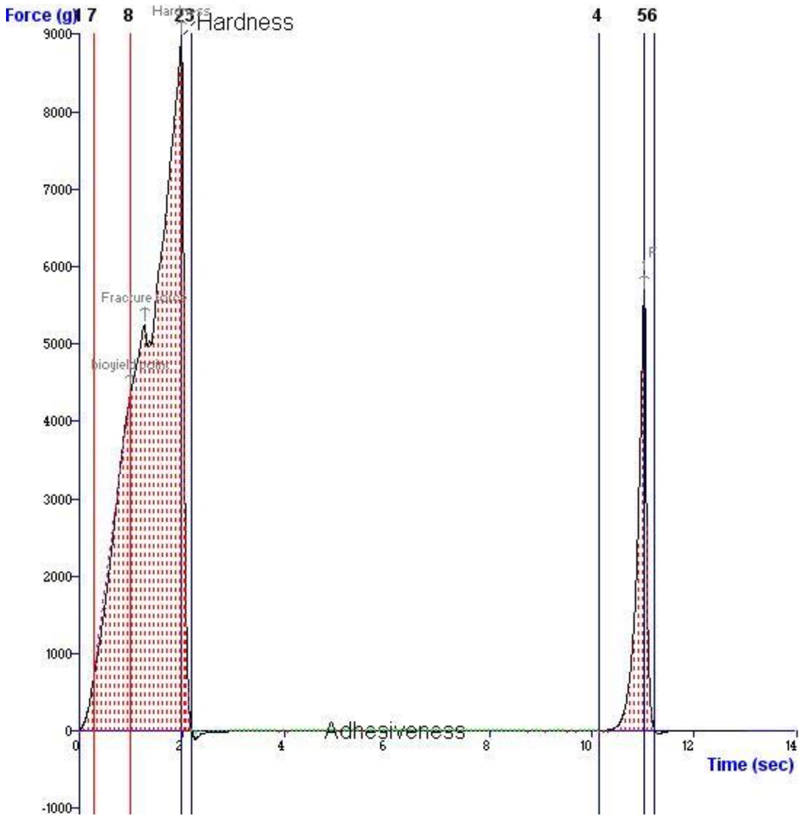


Fig. 3 Example of a force-distance curve obtained by the modified Texture Profile Analysis (TPA) test's script. The red line between the 7th and 8th anchors indicates the first curve's slope (Young's module), as described in Contador et al. (2015).

## 3.2- Sata SRL's sensory training and application of new methodologies recently introduced in the sensory science

### *3.2.1 Sensory training*

Even though many of the recently introduced sensory methods do not require training of assessors, it was necessary to introduce the sensory training of Sata srl's employees as some of the quality assessments were performed under a longitudinal study using conventional methods (e.g.

quantitative tests using scales compliant to ISO 4121-2003 (ISO, 2003), such as those under the marketing strategy “Branding”. Around 18 employees were invited to be part of the Sata SRL’s panel and were subjected to theoretical lessons imparted by Professor Cristiana Peano and by the apprentice doctoral student regarding sensory physiology and quality attribute’s definitions. For each crop subjected to the trials a technical sheet was provided with relevant specific attribute’s definitions. The practical lessons included the use of sensory standards (table 4) in different concentrations to train and test the discrimination and classification ability of assessors, as recommended by ISO 8586 (ISO, 2012) and through the use of conventional methods such as the “duo-trio” and “triangle” tests. Finally, prior to the quality assessments, assessors were trained to score product’s attributes according to a commercial reference, individuated for each fruit species subjected to the trials. Most of the fruit provided came from the Sata SRL’s retail client Pam Panorama S.p.A., which sponsored the training and some of the quality assessment performed in this project alongside with the Ph.D. programme funding.

| | **Sensory standards supplied by AROXA™ (Cara Technology, Leatherhead, UK)** | **Descriptors** |
|---|---|---|
| **Taste** | sodium chloride | salty taste |
| | fructose and sucrose | sweetness |
| | sucrose octaacetate | bitterness |
| | citric acid | sourness |
| | monosodium glutamate | umami taste |
| **Odour and aroma notes** | cis-3-hexenol | freshly cut grass |
| | 2-aminoacetophenone | fruity, grape-like odour |
| | dimethylsulfide | rotten vegetables |
| | geraniol | floral odours |
| | methyl thioacetate | cooked vegetables |
| | ethylphenyl acetate | honey |
| | geosmin | earthy notes |

| | | |
|---|---|---|
| | nonanal | dried grass or cucumber skin |
| | benzaldehyde | almond flavour |
| | ethyl hexanoate | pineapple, tropical fruit |
| | trans, cis-2,6-nonadienal | cucumber or watermelon |
| | isoamyl acetate | banana |
| | 2-isobutyl-3-methoxypyrazine | herbaceous, peper, earthy notes |
| **Tactile sensations** | tannic acid | astringent |
| | ferrous sulphate | metallic |

Table 4. List of compounds acquired for panelist's training

### *3.2.2 Application of new methodologies recently introduced in the sensory science*

After a long period of bibliographic research, it was decided to focus on two emerging sensory methods: The Projective mapping with trained assessors and the Check-all-that-apply (CATA) with consumers, with the latter being also followed by the Penalty analysis in order to link attribute perception to the acceptance of a product. Those methods are already largely employed in the sensory sector as they allow users to characterize products and investigate attribute's perception in an easier way by exploiting our more natural capability of judging products by comparison rather than evaluating them on an absolute scale (Valentin et al., 2012). Here an example how assessors were instructed to perform the projective mapping:

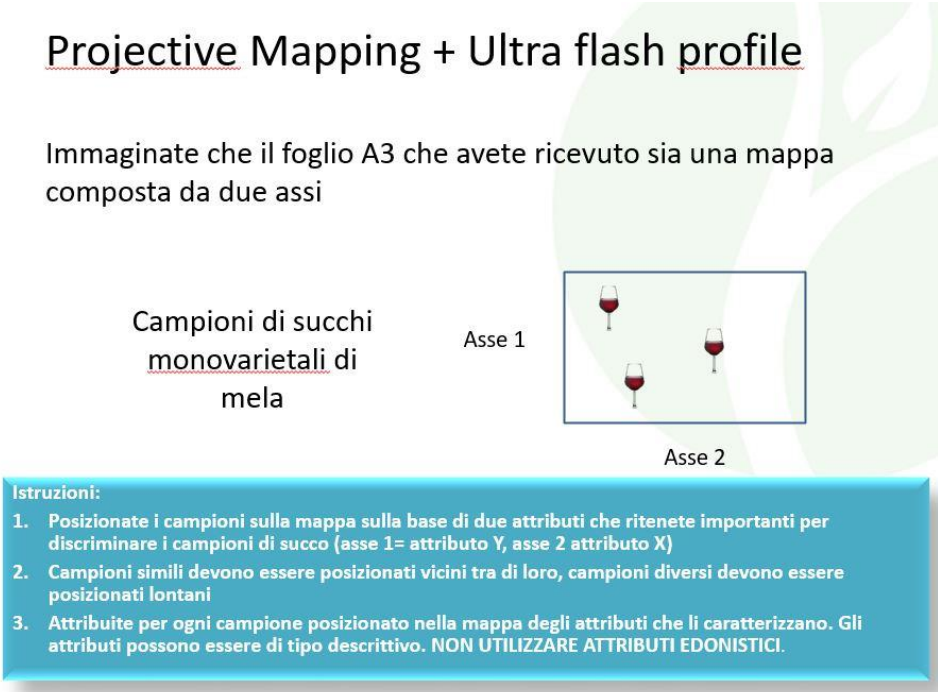


Figure 4 A picture of the power point slide presented to SATA SRL's assessors in order to perform the projective mapping method of monovarietal apple juices

However, at the same time the new methods present room for improvement as there are several ways in which the sensory tests can be prepared and presented to assessors and, in addition, data can be treated with different statistical techniques, which can represent a potential source of arbitrariness when evaluating the results, leading to different or misleading conclusions from a same set of data (Jaeger et al. 2013).

Therefore, for what concerns the preparation step of sensory tests, special attention was dedicated to the selection of attributes that were brought to be part of questionnaires or lists that were given to panelists prior to the test. In particular, different processes that involved data mining (example of results displayed in fig. 5) or qualitative research such as focus group (example of results displayed in fig. 6) were adopted in order to ensure that only relevant attributes were introduced to the tests. The choice between the former or the latter approach depended on how much information of products was available in the web, since this is a precondition to use the data mining process. Moreover, to obtain a correct interpretation of results, a relevant part of this work concerned the use of statistical analysis to validate sample's attributes, and therefore, the step 2 of this project was very dependent and connected with step 3, where univariate and multivariate models were studied and tested on data.

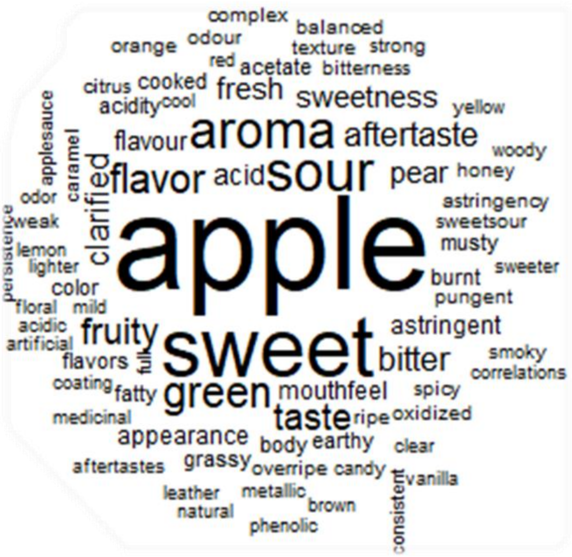


Fig. 5 The word cloud represents the frequency of attributes that were counted through a data mining process of several articles based on quality assessments of apple juices. This process was performed to prepare the list of attributes to be used during a projective mapping test of apple juices.


Fig. 6 The word cloud represents the frequency of terms obtained from a focus group to select relevant attributes to be part of a Check-all-that-apply questionnaire for a kiwi-berry quality assessment.

## 3.3- Study and application of statistical tools to handle data issues concerning horticultural products assessments

From a statistical point of view, the quality assessments of each marketing strategy were performed following a similar procedure: the use of univariate techniques to individuate differences among samples for each sensory attribute and/or analytical parameters, and the use of multivariate techniques to summarize the quality assessment results and to enable the identification of more complex relationships among samples and attributes. Also, regression techniques were employed in order to further investigate the relationship among selected attributes from the analysis of the previous steps and the overall liking scores obtained from the panel or the consumer test assessment. The criteria to choose the statistical techniques involved their ability to deal with different critical aspects concerning the samples (horticultural products with a high degree of variability within the same batch), the goal of the marketing strategy (longitudinal or vertical quality assessment of samples), and the type of data (continuous or discrete data). In all assessments performed in this project the type of data has introduced several aspects that needed to be handled. Analytical and conventional panel test sensory methods often provided to our experiment continuous data, while sensory methods such as CATA and Projective mapping provided counted or categorical data, hence, the use of statistical tools that deal with parameters of different nature was key to perform an integrated quality assessment. Also, the relationship among parameters and sensory attributes was another critical issue because it is known to be very heterogeneous, as it can be linear, highly collinear, or non-linear at a same experiment (Lombardo, 2011, Dias et al., 2011), which may require the use of techniques that deal with multicollinearity or are model-free by nature, meaning that they allow to set different relationship among parameters at the same time. Moreover, it is well known that the introduction of sensory methods leads to the introduction of dependent data as assessors, being them consumers or panelists, represent a random factor across samples or across time within a same sample (Kuznetsova, 2015). Differently from fixed factors, where specific levels are chosen for a treatment variable, and the same levels can be replicated in other experiments, random factors present levels that are chosen randomly from the population of all possible levels. As a result, future replications of the experiment might or might not select this exact same level (e.g. sensory tests conducted in other laboratories). The reason to consider assessors as a random factor is based on our interest to extend the results to the population where they come from rather than account for their specific estimate’s effects (Kuznetsova et al., 2014). This requires the use of proper models such as the mixed models, which are able to deal with fixed and random factors and account for the variability introduced by each assessor. Moreover, the same approach may be extended for sample's replicates if served separated (e.g. longitudinal study of a brand's quality), as horticultural samples are prone to biological heterogeneity during the season (Kusnetsova, 2015).

In Figure 6, we summarize how data was treat in our assessments. It is clear that the introduction of sensory data the assessment increases the quality assessment complexity as it introduces data of different type, which explains the use of different statistical methods.

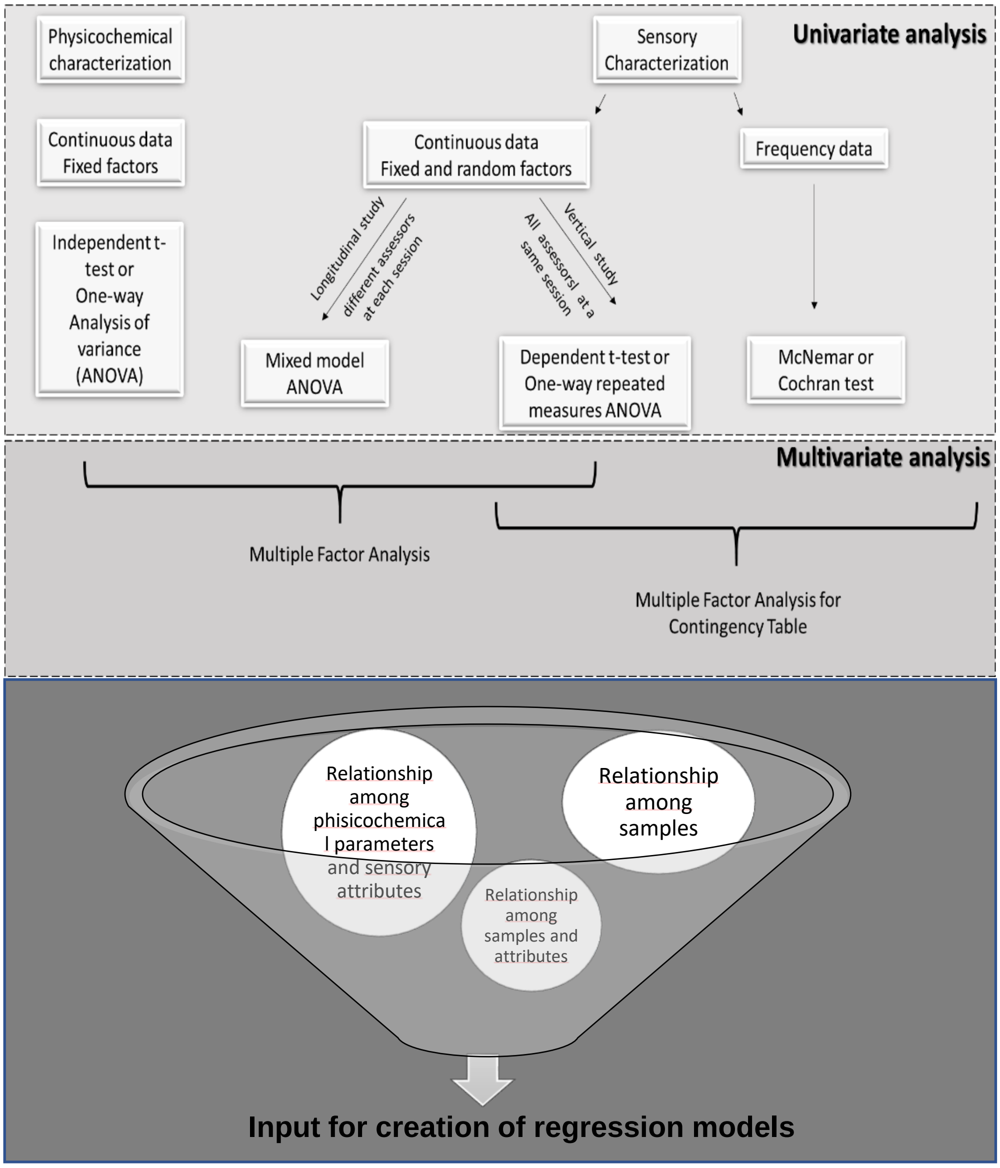


Figure 6- Flowchart that represents the different steps of the quality assessments used to investigate quality of products under the 3 marketing strategies.

To conclude, all models were created with the statistical software “R studio” (R Studio, 2018). The use of this type of software was essential to perform the abovementioned study as it is an open software where users can dispose of a high number of models that are available in several packages. Moreover, the number of packages is always increasing as it is possible to users to contribute to the software’s structure. Some of the main models employed in this research were:

- The multiple factor model is a non-constrained multivariate model that extracts latent factors to summarize samples’ information through a dimension-reduction process, with the additional feature (compared to principal component analysis) of assessing datasets where variables are structured in groups, therefore, it is a model useful to analyze multicomponent parameters, such as texture and taste (Giuggioli et al., 2020)
- The partial least square model is a constrained multivariate model that separates the dataset into dependent and independent variables. By doing this the model is able to extract the latent factors accounting for as much of the dependent factor variation as possible while modeling the responses well. Therefore, the model cand be used to perform predictions avoiding multicollinearity problems (Mendes da Silva et al., 2021)

## 3.4- The main results of the Ph. D. program: the 3 articles

In this thesis, it was decided to present the results obtained of 3 articles, where each article represent one of the abovementioned marketing strategies:

1- The developed quality assessment of a retail apricot brand: this article displays a quality assessment methodology to highlight how varieties may affect the quality standardization of a brand. It takes into account the summer perishable crop apricot, where the use of different varieties is the only possible way to ensure the minimum commercial period required by retail clients. The quality assessment consists on a longitudinal study, where varieties that are sequentially harvested are compared, especially in terms of sensory quality. We have shown that with the use of proper techniques, it is possible to model the uncertainty of human judgment and different relationships between quality attributes and the overall liking to identify strong quality indicators. The developed methodology is currently employed to assess quality of Sata SRL's retail clients and to identify the most important quality indicators for their brands.
2- The sensory characterization of single-cultivar apple juices: this article displays a quality assessment employing the projective mapping method to identify the main sensory descriptors of apple juices. In particular, we share instructions to perform a data mining process to exploit available data and create assessor's vocabulary, and we propose a statistical method to validate the most important sensory attributes of each juice. This article offers the sector a method to reduce the arbitrariness of result's interpretation.
3- The pre-harvesting quality assessment of maturity and ripening indices of kiwi-berry fruits (*A. arguta*): in this article, we display a new methodology to investigate which analytical parameters are more reliable to describe the harvesting quality of kiwi berries. In particular, we show how the use of models that take into account composite indicators are suitable tools to summarize a quality attribute influence on the harvesting quality. With this article we

offer the sector a methodology that can be employed when the quality assessment involves attributes that are summarized by multiple analytical parameters (e.g. colour, texture).

# 4- A novel statistical approach to assess the quality and commercial viability of a retail branded perishable fruit

This chapter is dedicated to the article publication:

Mendes Da Silva, T., Peano, C., & Giuggioli, N. R. (2019). A novel statistical approach to assess the quality and commercial viability of a retail branded perishable fruit. CyTA - Journal of Food, 17(1), 581–592. https://doi.org/10.1080/19476337.2019.1621389

# A novel statistical approach to assess the quality and commercial viability of a retail branded perishable fruit

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**ABSTRACT**

Few studies have investigated sensory quality in multi-varietal fruit brands due to challenges in making comparisons between varieties harvested sequentially throughout the season. Sensory data are collected in crisp form and analysed using a great amount of numerical data. However, human perception is vague and an assessor's opinion comes in linguistic form. The purpose was to assess the sensory quality of branded apricot using a novel statistical approach. Physicochemical and sensory attributes were determined for two consecutive commercial seasons. Univariate and multivariate models were applied in order to assess quality stability and to create a prediction model. The brand was affected by the presence of different cultivars and the multiple factor analysis demonstrated aroma and juiciness as the most differentiated parameters, while univariate analysis highlighted hardness and mealiness. Use of expert knowledge mixed with information from sample data enabled the development of a fuzzy model. Investigation with consumer test is needed.

**ARTICLE HISTORY**
Received 28 January 2019
Accepted 13 May 2019

**KEYWORDS**
fruit quality; sensory analysis; brand; fuzzy; apricot

**PALABRAS CLAVE**
calidad de la fruta; análisis sensorial; marca; difuso; albaricoque

## Novedoso enfoque estadístico para evaluar la calidad y la viabilidad comercial de una fruta perecedera de marca minorista

**RESUMEN**

Pocos estudios han investigado la calidad sensorial en marcas de frutas de múltiples variedades debido a las dificultades para realizar comparaciones entre variedades cosechadas de forma secuencial a lo largo de una temporada. Generalmente, los datos sensoriales se recopilan de forma precisa y se analizan utilizando una gran cantidad de datos numéricos. Sin embargo, la percepción humana suele ser vaga y la opinión del evaluador se presenta en forma lingüística. El propósito del presente estudio fue evaluar la calidad sensorial del albaricoque [durazno] de marca empleando un enfoque estadístico novedoso. Así, durante dos temporadas comerciales consecutivas se determinaron los atributos fisicoquímicos y sensoriales de los albaricoques. Para ello se aplicaron modelos univariados y multivariados con el fin de evaluar la estabilidad de la calidad y crear un modelo de predicción. Se constató que la marca se vio afectada por el uso de diferentes cultivares; en este sentido el análisis factorial múltiple demostró que el aroma y la jugosidad son los parámetros de la fruta que más se diferencian, mientras que el análisis univariado destacó la dureza y la consistencia harinosa de la fruta. El uso de conocimiento experto combinado con la información proveniente de los datos de muestra permitió desarrollar un modelo difuso. Es necesario realizar investigaciones que incluyan pruebas entre consumidores.

## 1. Introduction

Retail branded products have been successfully commercialized in recent years (Geyskens, Keller, & Dekimpe, 2018) in developed markets such as Europe and North America. However, there is still a huge variation on private-label development, with Italy presenting only 17% of the share, which is nearly half the amount of Switzerland (45%) (Report, 2014). Different categories of food may create differences in market shares along EU countries. Private-label success is known to be the strongest in commodity-driven areas where consumers perceive little or no differentiation (Report, 2014). Thus, to improve the demand of branded products, retailers must have a keen understanding of local market dynamics and consumer response to different categories of food, especially with fresh products.

Among fresh products, the brand has been scarcely applied to fruit (Rickard, Schmit, Gómez, & Lu, 2013) due to its high variability, creating a challenge for quality standardization and marketing strategies. Currently, there are few successful exceptions, such as apples, bananas and kiwifruit, whereby a single variety is usually marketed during the entire season and usually takes the place of a brand's name (Rickard et al., 2013). In apples, for example, variety names are used to allude to sensorial perception and are employed in order to communicate quality of the brand (e.g. Honeycrisp) (Rickard et al., 2013). However, this approach is not feasible for summer perishable crops, such as stone fruit and apricots. In this case, more varieties need to be employed on a brand since each of them are present in the market for a short period, making it difficult for consumer loyalty to a specific phenotype. Moreover, this situation cannot be resolved only by importing a specific variety, especially due to the short postharvest life of the species (Gatti, Defilippi, Predieri, & Infante, 2009). Using different varieties in a single brand in order to meet the retail requirements of a longer shelf life might lead to inconsistent quality within the brand. Therefore, the only solution to promote and retain consumer loyalty is to select similar varieties related to aesthetic and sensorial qualities.

Relatively few studies have investigated sensorial perception issues in multi-varietal brands, due to the difficulty of making comparisons between varieties that are harvested sequentially throughout the season. Sensory analysis plays a very important role on quality assessment (Alonso, Paquin, & Mangin, 2002) but sensory data are usually collected in crisp form and analysed statistically using a great amount of numerical data. This might not be effective since human perception is always vague and the assessor's opinion by nature comes in linguistic form. Therefore, it is more realistic to carry out linguistic assessments using linguistic variables instead of numerical values (Mukhopadhyay, Majumdar, Goswami, & Mishra, 2013). According to earlier studies, fuzzy logic is a useful tool that can be employed when conducting analyses on sensory data of many food products (Tahsiri, Niakousari, Khoshnoudi-Nia, & Hosseini, 2017). It takes into account uncertainty since it allows a crisp value to be in a state other than a binary position (true or false) by attaching a credibility that it belongs to a set of elements (fuzzy set) (Bouyssou, Dubois, Pirlot, & Prade, 2006). Fuzzy logic also deals with linguistic variables since fuzzy rules are set in natural language that will be converted into numerical data by applying the fuzzy set theory (Kaushik, Gondi, Rana, & Srinivasa Rao, 2015). By doing that, relationships between linguistic variables and acceptance, or rejection of a product, may be assessed (Kaushik et al., 2015) without neglecting uncertainty derived from an assessor not being able to find an exact value for a variable. This includes firmness or overall liking, which may be expressed as "high", "medium" or "low", rather than with numbers.

Therefore, the purpose of this work was to assess the ongoing quality of a retail branded apricot, characterized by three different sequentially harvested varieties during two seasons. This was performed by using univariate and the novel multivariate approach.

## 2. Materials and methods

Retail branded apricots coming from the same northern Italian supplier, from Emilia Romagna, were analysed during two consecutive commercial seasons (Year 1 and Year 2), from the end of July to the beginning of August. The brands were composed of Lady Cot (LC), Faralia (FR) and Farbaly (FB) varieties due to their similarities in colour and shape but different by time of harvesting. Two consecutive samplings were made for each variety, totalling six samples (LC_1, LC_2, FR_1, FR_2, F_B1 and FB_2) for Year 1 and Year 2. Samples were analysed for physicochemical parameters, colour indexes, and sensorial analysis.

### 2.1. *Physicochemical parameters and colour indexes*

Twenty replicates for each sample were analysed with a universal sizer (Turoni srl - universal calibrator). Total solid solubles (Brix) and firmness were determined for 20 replicates according to OECD guidelines (OECD guideline, 2009) with a digital refractometer (Atago, mod. PAL-1) and a fruit texture analyser (Turoni srl, mod. 53220). The titratable acidity (TA) of apricot juice was determined in triplicate by titration with 0.1 N NaOH to pH 8.1 and expressed as g/100 g of malic acid. The ratio of Brix and TA (Ratio B.S.) was calculated, as well as BrimA index as proposed by Stanley and others (2014). Colour was measured with a colorimeter (Konica Minolta, mod. CR-400) upon two sides (the more colourful and the less coloured side) in the equatorial zone of 20 fruits. The L*, a* and b* were recorded with Konica Minolta software (SpectraMagic NX software). According to earlier studies, the red colour of apricots seemed to catch consumer's eyes and contributed to visual appearance (Fan, Zhao, Wang, Cao, & Jiang, 2017). Therefore, deriving from L*, a* and b*, other colour indexes previously tested were calculated in order to enhance sensitiveness of colour evaluation (Cristina, 2014; Manera et al., 2013; Pathare, Opara, & Al-Said, 2013):

- C* : $\sqrt{a^{2*} + b^{2*}}$
- h* : $\tan^{-1} \frac{b^*}{a^*}$
- CI: $1000 \times a^*/L^* \times b^*$
- MIC: $L^* \times a^*/b^*$
- COL: $2000 \times a^*/(L^* \times C^*)$
- H index: $(180 - h)/(L^* + C^*)$

### 2.2. *Sensorial analysis*

Ten panellists from Sata srl (Alessandria, Italy) were selected and trained in sensory evaluation of apricots as recommended by ISO 8586 (ISO, 2012). Panellists were trained by discussing the definition of quality parameters selected for sensory evaluation, explaining the score sheet and method of scoring. The analyses were done between 3pm and 5pm. Two different continuous scales compliant to ISO 4121-2003 (ISO, 2003) were used: a hedonic scale with one end, "dislike extremely", and the opposite end, "like extremely", for an overall liking assessment. A continuous intensity scale with one end, "extremely low intensity", and the opposite end, "extremely high intensity", was used to assess descriptive sensory attributes from apricot samples during the two seasons. In this work, panellists were asked to not consider aspects and colour of the product, but only to focus on taste, texture and aroma. For the overall liking assessment, panellists were trained to use the variety, Orange rubis, as a reference standard, which is known to be a benchmark of excellence among modern Italian produce without disappointing storability expectations (Piagnani & Bassi, 2013). Other than the overall liking assessment, the descriptive sensory analysis was assessed in terms of hardness, mealiness, juiciness, sweetness, sourness, and aroma. Panellists were presented with eight apricot slices from four different fruits.

### 2.3. *Statistical analysis*

All data sets were analysed with R software (R Core Team, 2018) using "FactoMiner" (Le, Josse, & Husson, 2008) and "sets" (Meyer & Hornik, 2009) packages for the multivariate analysis, and "nlme" (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018) and "lsmeans" (Lenth, 2016) packages for the univariate analysis. A linear-mixed model was used to analyse data, using samples as a fixed effect, and panellists as a random effect. Data were expressed as means. Results were considered to be significant at the level of $p < 0.05$. All parameters were analysed with the Multiple Factor Analysis (MFA) in order to evaluate more complex relationships between parameters and to identify which of them were better related to overall liking. Twenty-one different parameters were scaled and grouped into new continuous sets of data named "physicochemical", "colour" and "sensorial attributes". Overall liking was scaled and classified separately from sensorial data as a continuous supplementary group and two more supplementary categorical groups named "Varieties" and "Year" were added to group samples (observations) by variety and year in order to obtain their centroids. A scree plot was produced in order to decide how many dimensions keep in the model.

Two different models were created based on the Fuzzy logic in order to predict Overall Liking. One model (fuzzy model 1) was based only on distinctive sensorial descriptors and parameters better related to Overall Liking on MFA analysis, while the second model (fuzzy model 2) was based on MFA results but also considers the most significant parameters of univariate analysis.

Fuzzy models are particularly useful in the cases where human knowledge is available and where there is not enough information to feed traditional mathematical models (Tagarakis et al., 2014). In this work, the fuzzy inference system was applied for the classification of 12 samples. The Mamdani method first converts process states into linguistic variables and uses them as inputs to create rules (Alavi, 2013). In order to create linguistic variables, selected parameters and overall liking were converted into membership functions (fuzzy sets). The number of fuzzy subsets chosen is problem dependent but usually, they are three or five and are almost always an odd number (Eberhart & Shi, 2007). Therefore, membership functions were set using three different levels: "scarce/low", "ok/intermediate" and "excellent/high", and numerical values (fuzzy subsets) were assigned to each level: scarce/low = 1, good/intermediate = 5 and excellent/high = 9, as suggested by experts. It is worth remembering that fuzzy subsets have overlap regions with neighbouring classes (Papageorgiou, Aggelopoulou, Gemtos, & Nanos, 2018) and, in this work, overlap regions were determined by standard deviations of measured data. Membership functions were normalized, meaning that the highest part of each function equals to one (Eberhart & Shi, 2007).

Many studies have investigated how to formulate rules but expert knowledge is still the most commonly used system (Alavi, 2013). Thus, the shape of membership function and IF-THEN rules were established based on expert knowledge on quality evaluation from Sata srl and the Department of Agricultural, Forest and Food Sciences (DISAFA) at the University of Turin.

In order to determine the degree of credibility of propositions (e.g. overall liking is high), an implication process must take place. After rules were set, fuzzy data provided by the fuzzification step were subjected to the Mamdani inference engine, which implication method uses MIN operator and aggregates all fuzzy sets obtained with MAX operator. When a rule is evaluated with the MIN operator, the minimum membership value of the antecedent's parts is chosen. While with the MAX operator, the outputs of each rule are mixed to obtain a single fuzzy (the resulting fuzzy sets of each activated rule are summed) (Papageorgiou et al., 2018). Defuzzification was done with the centre of gravity method (Alavi, 2013) in order to convert the fuzzy output set to a crisp number.

In order to evaluate goodness of both fuzzy models, predicted data were compared with real data (overall liking scores) and $R^2$ determination coefficient was determined, along with the Pearson coefficient and its significance at the level of $p < 0.05$. A Multiple Linear Regression (MLR) model was applied to the same parameters of both fuzzy models. $R^2$, Adjusted $R^2$ and significance at the level of $p < 0.05$ were assessed. Coefficients of both MLR and developed fuzzy models were compared. Existence of multi-collinearity on MLR models was evaluated by calculating the Variance Inflation Factor (VIF), where values greater than 5 will indicate the existence of multi-collinearity and values greater than 10 will indicate severe problems of multi-collinearity (Dias, Peres, Barcelos, Sá Morais, & Machado, 2011). Cook's distance, which is the most well-established method for assessing the influence of individual data cases, was also calculated.

## 3. Results and discussion

### 3.1. *Sensorial evaluation of samples*

There were significant differences between samples on overall liking scores during Year 1 (Figure 1), with FR1 being appreciated more than FB2, while during Year 2 there were no significant differences. Overall liking scores were generally low for both years, indicating poor taste and aroma quality of fruit. LC, FR and FB are modern apricot cultivars, which are distinguished by their large size, intense orange skin colour and red blush. In the last years, the improvement of the aesthetic characteristics occurred to the detriment of the flavour (taste and aroma) (Pagnani & Bassi, 2013), leading to increased consumer dissatisfaction. In this work, sensory descriptive attributes and physicochemical characteristics were important to have a better understanding of the poor quality of samples.

Several attributes of FB and LC samples were significantly different from FR samples (Figure 2). For both years FB samples presented lower scores of hardness and higher scores of mealiness, while in Year 1 FB_2 samples presented also lower scores of aroma. LC samples were characterized by lower scores of sweetness and higher scores of sourness during Year 1. Juiciness seemed to also be a distinctive factor for both FB and LC varieties: FB samples presented lower scores for both years when compared to at least one of the FR samples, while LC_1 sample was considered less juicy than FR in the first year. The lowest scores found for LC samples regarding sweetness in this work may have had an important impact on overall liking since this attribute is related with product taste (Fan et al., 2017). However, even though sweetness is known to correlate well with overall fruit quality, taste and acceptability (Infante, Meneses, & Defilippi, 2008), other studies suggested that texture properties altered by chilling injury (Stanley et al., 2014) or due to unripen stage (Valentini, Mellano, Antonioni, & Botta, 2006) may have a greater impact on apricot quality than sweetness. It is well documented that apricots develop chilling injury symptoms when stored below 7°C, such as mealiness, loss of juiciness or gel breakdown (Stanley, Prakash, Marshall, & Schröder, 2013), and unripe fruit are considered harder and less juicy (Valentini et al., 2006). In Table 1, it is possible to identify which sensorial parameters were the sample's biggest differentiators by assessing $p$-values resulted from the analysis of variance of mixed models. In this work, hardness and mealiness presented lower $p$-values, meaning the assessor's average scores were more variable among samples for texture attributes than taste or aroma.

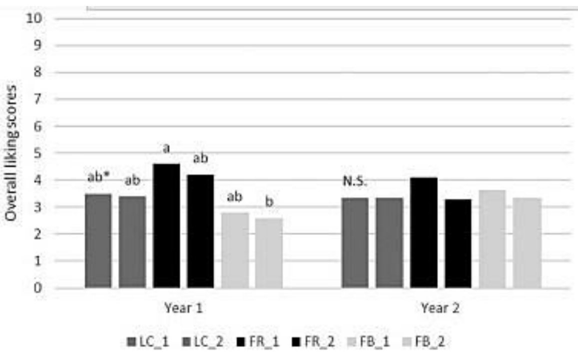


Figure 1. Overall liking scores of apricot samples Lady cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) during Year 1 and Year 2.

* Different lower-case letters (a-b) show significant differences among treatments ($P \leq 0.05$). Capital letters (N.S) show absence of significant differences ($P \leq 0.05$) within treatment.

Figura 1. Puntuaciones generales de agrado de muestras de albaricoque Lady cot (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) durante el año 1 y el año 2.

* Las diferentes letras minúsculas (a – b) muestran la presencia de diferencias significativas entre los tratamientos ($P \leq 0.05$). Letras mayúsculas (N.S) indican la ausencia de diferencias significativas ($P \leq 0.05$) entre los tratamientos.

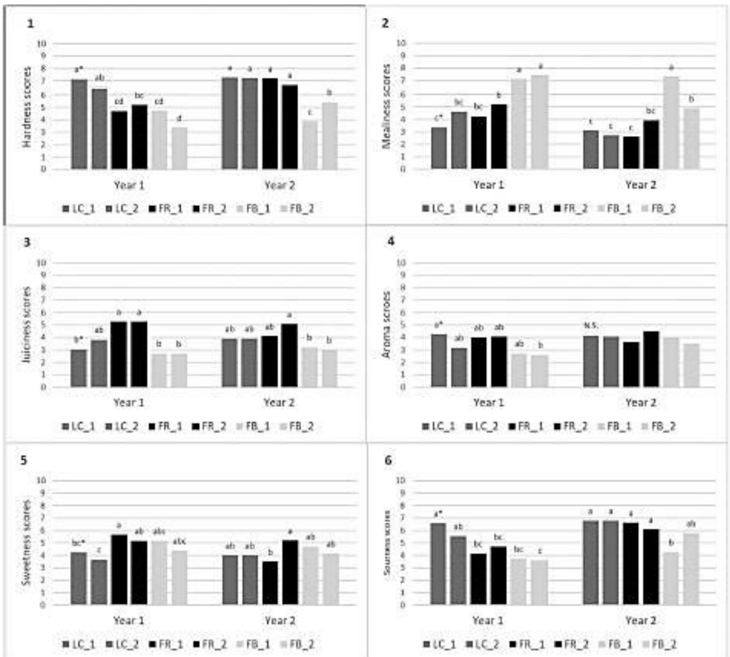


Figure 2. Hardness (1), mealiness (2), juiciness (3), aroma (4), sweetness (5) and sourness (6) scores obtained from sensory analysis of apricot samples Lady cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) during Year 1 and Year 2.

* Different lower-case letters (a–b) show significant differences among samples ($P \leq 0.05$). Capital letters (N.S).show absence of significant differences ($P \leq 0.05$) within treatment.

Figura 2. Puntuaciones de dureza (1), harinosidad (2), jugosidad (3), aroma (4), dulzor (5) y acidez (6) obtenidas a partir del análisis sensorial de muestras de albaricoques Lady cot (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) durante el año 1 y el año 2.

* Las diferentes letras minúsculas (a – b) indican la presencia de diferencias significativas entre las muestras ($P \leq 0.05$). Las letras mayúsculas (N.S) indican la ausencia de diferencias significativas ($P \leq 0.05$) entre los tratamientos.

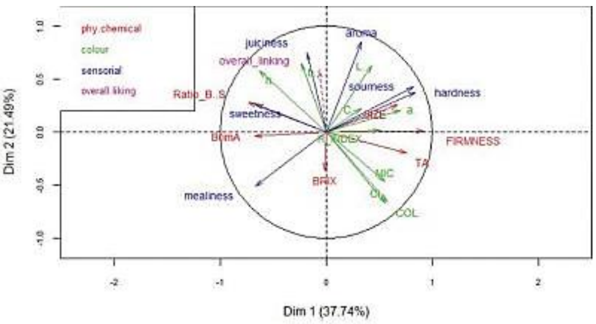


Figure 4. Biplot of physicochemical, colour and sensory original variables on the dimensions 1 and 2 after analysis on physicochemical, colour and sensorial attributes of apricot samples.

Figura 4. Biplot de variables fisicoquímicas, de color y sensoriales originales en las dimensiones 1 y 2 después del análisis de los atributos fisicoquímicos, de color y sensoriales de muestras de albaricoques.

It is also evident that °Brix was negatively correlated with overall liking, which is not expected for fruit products. This is probably due to the fact that, with exception of FR_1 Year 1 (13.2° Brix), samples with higher Brix values presented defects on texture properties, highlighted by the sensory analysis. °Brix values of samples (not shown), ranged from 10.0 to 13.3, with both samples LC from Year 2 presenting 13.3° Brix, and FB both samples from Year 1 presenting 13.2 and 13.1° Brix, respectively.

Firmness was orthogonal to overall liking, demonstrating that this attribute was not a good quality indicator of apricots. This result shows how analysing texture by only assessing firmness may not be exhaustive to have a better understanding on how this multicomponent attribute affects quality. Thus, more complex instruments should have been used in order to improve instrumental quality evaluation.

With regard to colour indexes, the most correlated parameters with a second dimension and thus, overall liking, were: L* and h*, positively and CI, COL negatively. Even though Index b* was very close to overall liking, it was not considered since its quality representation (data not shown) on the global axis was very low with a coefficient $\cos^2$ lower than 0,50. Both CI and COL indexes were previously applied to citrus and tomatoes to evaluate the de-greening and ripening stage, respectively (Cristina, 2014; Pathare et al., 2013). This represents the changing from green-yellow to orange-red colour, while the enhancing of h* values would indicate a yellowish colour of samples (Infante et al., 2008). Even though orange/red colour is indirectly related to the apricot ripening stage, the negative relationship between CI, COL and overall liking, along with the positive relationship between h* and overall liking, suggested that orange-red flushed apricots were not the most appreciated fruit. These results are not in agreement with Cristina's work (2014) where h*, COL and CI were considered to be good ripening indicators of different varieties of apricots. However, it confirms that variety selection based on aesthetic issues may contribute to consumer disappointment (Piagnani & Bassi, 2013).

In summary, it is clear how sensorial parameters are better related to overall liking than any other single parameter illustrated in Figure 4. This is true especially for those parameters that were not directly measured by any instrumental analysis such as aroma and juiciness. Juiciness is a very important quality attribute for fruit, depending on cultivar and ripening stage, and it enhances the perception of sweetness (Melgarejo et al., 2013). In fact, juiciness and sweetness correlated positively on the MFA biplot of variables, while aroma was positively correlated to sourness, which is found to be essential in fruit as a regulatory factor to obtain an optimal flavour (Huang et al., 2018). For what concerns mealiness, contradictory results came from multivariate and univariate statistics. Multivariate did not show an important relationship between mealiness and overall liking (mealiness's correlation coefficient on second dimension was not significant) while univariate analysis indicated significant differences for this attribute between most appreciated (FR_2 Year 1) and less appreciated (FB_1 Year 1) samples. This is probably due to the non-linear relationship that might exist between sensory attributes in some cases (Lombardo, 2011), and may not be detected by MFA analysis, which relies on linear combinations of original parameters when producing global axes (dimensions) that maximize the global data variance (Vilor-Tejedor et al., 2018).

Some authors may state that mealiness and loss of juiciness represent the same condition, while others may emphasise the difference between the presence of soft and dry fibre (woolliness) and a sandy texture (mealiness) (Stanley et al., 2013). However, development of both parameters is highly dependent on cultivar physiology and how it responds to storage temperature (Stanley et al., 2010), while aroma is influenced by pre and postharvest factors and determined genetically (Gatti et al., 2009). Overall, varieties were well discriminated, especially in terms of sensorial parameters. This should be taken into account when creating a branded product marketing image.

With the exception of LC samples, MFA biplot of scores and centroids (Figure 5) shows that samples FB and FR were globally more similar among each other when compared with LC. These results were expected since generally late varieties present lower values of firmness and TA and higher values of brix, which might then influence sensorial parameters (Amoriello, Ciccoritti, Paliotta, & Carbone, 2018).

In both MFA biplots of scores and variables, it is evident that the most appreciated samples came from FR samples, being centroid of this sample significantly correlated with dimension 2 and placed near to overall liking. Farbaly samples are positioned very close to mealiness and in the opposite side of hardness,

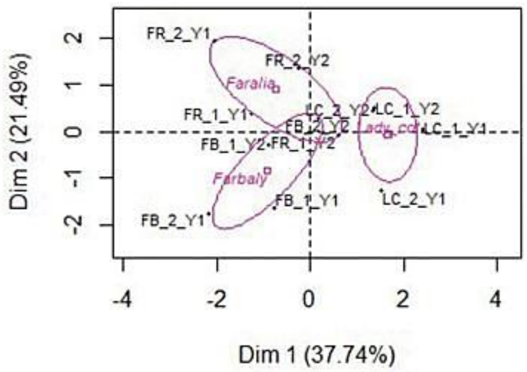


Figure 5. Biplot of the scores and confidence ellipses plotted on the first 2 dimensions after analysis on physicochemical, colour and sensorial attributes of all apricot samples. Samples of Lady Cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) of Year 1 and Year 2 are indicated with dots. 95% Confidence intervals were calculated around centroids of factor scores for each variety (Lady Cot, Faralia and Farbaly).

Figura 5. Biplot de las puntuaciones y elipses de confianza representados en las 2 primeras dimensiones después del análisis de los atributos fisicoquímicos, de color y sensoriales de todas las muestras de albaricoques. Las muestras de Lady Cot (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) del año 1 y el año 2 se indican con puntos. Los intervalos de confianza del 95% se calcularon alrededor de los centroides de las puntuaciones de los factores para cada variedad (Lady Cot, Faralia y Farbaly).

meaning that those varieties were distinguished by being mealy and soft, while LC samples are better described by higher values of hardness and sourness, as well as their instrumental indicators, TA and firmness. These results are in accordance with the univariate analysis.

In Figure 6, it is possible to observe that overall, brand quality represented by all varieties was similar among Year 1 and Year 2, even though it is clear that variability during Year 1 was greater than Year 2. It is also suggested that the brand had a greater overall quality during Year 2, demonstrated by its positive v-test value of 1,169 (Lebart, Morineau, & Piron, 1995).

### 3.3. Fuzzy model

Two different Fuzzy models were developed. Fuzzy model 1 considered only the two most correlated (juiciness and aroma) to overall liking variables provided by MFA analysis. Fuzzy model 2 considered the results of the univariate analysis.

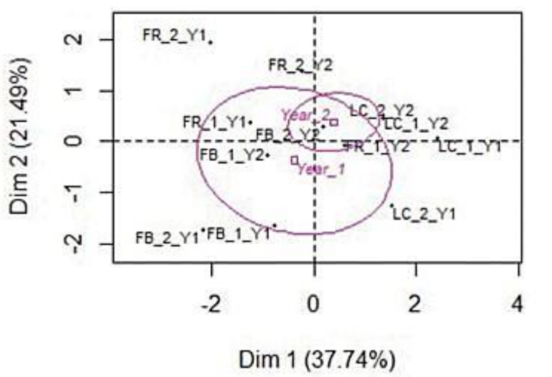


Figure 6. Biplot of the scores and confidence ellipses plotted on the first 2 dimensions after analysis on physicochemical, colour and sensorial attributes of all apricot samples. Samples of Lady Cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) of Year 1 and Year 2 are indicated with dots. 95% Confidence intervals were calculated around centroids of factor scores for each Year (Year_1 and Year_2).

Figura 6. Biplot de las puntuaciones y elipsis de confianza representados en las 2 primeras dimensiones después del análisis de los atributos fisicoquímicos, de color y sensoriales de todas las muestras de albaricoques. Las muestras de Lady Cot (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) del año 1 y el año 2 se indican con puntos. Los intervalos de confianza del 95% se calcularon alrededor de los centroides de las puntuaciones de los factores para cada año (año_1 y año_2).

Thus, for fuzzy model 2, hardness was chosen as the input variable other than juiciness and aroma since this descriptor presented a lower *p*-value on the univariate analysis. Unlike mealiness, it is more informative, taking into account both softening caused by chilling injuries and undesired firmness values due to the unripen stage. The shape of membership functions was chosen to be gaussian for input variables and triangular for overall liking for both models (Figures 7 and 8). Rules were set as described in Table 2 for fuzzy model 1 and Table 3 for fuzzy model 2.

Determination of membership functions in terms of shape, overlapping regions and boundaries has a great impact on a model's output and is problem dependent. One way to improve a model's accuracy is to relate to sample statistics such as averages and standard deviations (Alavi, 2013) and to consider the sample's nature. Triangular and trapezoidal are commonly used for membership functions since they are simple (Papageorgiou et al., 2018). However, using triangular or trapezoidal functions for agriculture products may not be suitable since these products have higher variability within the sample (Alavi, 2013). Thus, gaussian membership functions for input variables might have contributed to enhance the accuracy of fuzzy model. In this study overlapping regions were determined by standard deviations of input variables given by panellists on sensory evaluation while boundaries were determined by combining expert knowledge with sensorial data from this study.

From Tables 4 and 5, it is possible to observe that both fuzzy models classified FR samples from Year 1 with the highest predicted overall liking score, which is in accordance with real data from panellists. At the same way, FB samples from Year 1 presented the lowest scores.

The correlation study between predicted values of fuzzy model 1 and real data presented a significant Pearson's coefficient of 0.75 (*p*-value < 0.01) (Figure 9), and a determination coefficient $R^2$ of 0.57. This value was only slightly higher than the multiple linear regression (MLR1) that considered the same parameter's juiciness and aroma as input variables, which has presented an $R^2$ of 0.54, an adjusted $R^2$ of 0.44, and the model was significant (*p*-value 0.028). However, the MLR1 model did not comply with the MLR model considering the same parameters of hardness, juiciness and aroma (MLR2) was not improved by additional hardness. The MLR2 presented an $R^2$ of 0.56, an adjusted $R^2$ of 0.39 and was not significant (*p*-value 0.075).

MLR models require that dependent and independent variables satisfy many assumptions. Globally the data must have a linear behaviour and the independent variables should not show multicollinearity. Additionally, the model errors should follow a normal distribution, present homogeneity of variances and an independent strong autocorrelation between both input parameters may inflate the $R^2$ coefficient (Dias et al., 2011). In this work, VIF values of MLR1 and MLR2 models were 2.20 and 2.26, which do not indicate problems of multi-collinearity of data, although Cook's distance of both models indicates that sample FR_2_Year 2 was an influential point, meaning that residuals have patterns. It is well known that non-compliancy of MLR assumptions are probably related to the presence of outliers or existence of a non-linear relationship between dependent and independent variables (Bruce & Andrew, 2017). Use of different models to overcome non-linear relationships between sensorial data is widespread in literature (Di Natale et al., 2001; Stanley et al., 2013) since many sensorial systems display non-linear behaviour that may not be reliably modelled by using linear regression techniques (Lombardo, 2011). Among them, artificial neural networks are powerful techniques to deal with non-linear data (Dong

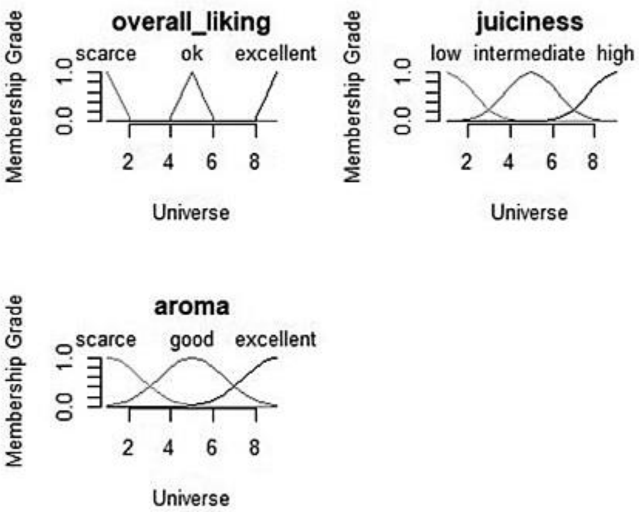


Figure 7. Developed membership functions of Overall liking, aroma and juiciness of fuzzy model 1.

Figura 7. Funciones de membresía desarrolladas de gusto general, aroma y jugosidad del modelo difuso 1.

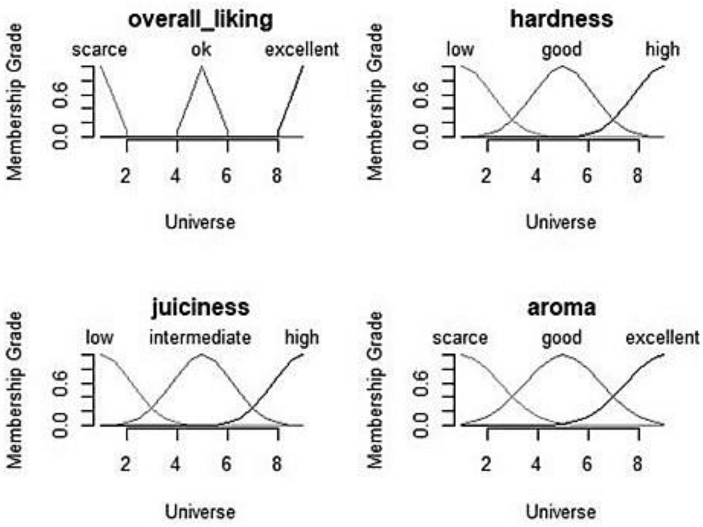


Figure 8. Developed membership functions of Overall liking, hardness, aroma and juiciness of fuzzy model 2.

Figura 8. Funciones de membresia desarrolladas de gusto general, dureza, aroma y jugosidad del modelo fuzzy 2.

Table 2. Fuzzy rules developed for aroma and juiciness of fuzzy model.

Tabla 2. Reglas difusas desarrolladas para el aroma y la jugosidad del modelo difuso.

| | Juiciness | | |
|---|---|---|---|
| Aroma | Low | Intermediate | High |
| Scarce | Scarce | Ok | Ok |
| Good | Ok | Ok | Excellent |
| Excellent | Ok | Excellent | Excellent |

et al., 2014) although they require large data sets for training data (Papageorgiou et al., 2018). Therefore, using the fuzzy model enabled the development of a classification model that might be useful when dealing with small samples without leaving aside non-linearity of data. In this work, even though R and $R^2$ values of fuzzy model 2 were not high, it is interesting to observe how it was possible to obtain an improvement of the first fuzzy model by adding the hardness parameter, which presented a different relationship with overall liking compared to juiciness and aroma (Figure 10). In fact, hardness presented a clear non-linear relationship, since higher and lower values of this parameter impacted negatively on overall liking scores, as shown in Table 3. In particular, higher values of hardness impacted more negatively than lower values of hardness on the assessor's overall liking score. The possibility to describe different relations by setting specific rules for each input parameter enabled fuzzy model 2 to improve fuzzy model 1. This was not observed when applying MLR, which requires that the relationship between dependent and independent variables is the same and linear. Therefore, the fuzzy model might be a useful tool when the collection of large datasets is limited and expert-knowledge is available to set the model's rules.

Table 3. Fuzzy rules developed for hardness, aroma and juiciness of fuzzy model 2.

Tabla 3. Reglas difusas desarrolladas para la dureza, el aroma y la jugosidad del modelo fuzzy 2.

| Hardness | Juiciness | Aroma | Overall liking |
|---|---|---|---|
| Intermediate values of hardness | Low | Scarce | Scarce |
| | Low | Good | Ok |
| | Low | Excellent | Ok |
| | Intermediate | Scarce | Ok |
| | Intermediate | Good | Ok |
| | Intermediate | Excellent | Excellent |
| | High | Scarce | Ok |
| | High | Good | Excellent |
| | High | Excellent | Excellent |
| High values of hardness | Low | Scarce | Scarce |
| | Low | Good | Scarce |
| | Low | Excellent | Scarce |
| | Intermediate | Scarce | Scarce |
| | Intermediate | Good | Scarce |
| | Intermediate | Excellent | Scarce |
| | High | Scarce | Ok |
| | High | Good | Ok |
| | High | Excellent | Ok |
| Low values of hardness | Low | Scarce | Scarce |
| | Low | Good | Ok |
| | Low | Excellent | Ok |
| | Intermediate | Scarce | Ok |
| | Intermediate | Good | Ok |
| | Intermediate | Excellent | Ok |
| | High | Scarce | Ok |
| | High | Good | Ok |
| | High | Excellent | Ok |

## 4. Conclusions

In this study, quality of retail branded apricots resulted variable during commercial life in two consecutive seasons due to the presence of different cultivars. This reveals how important the management of fresh produce is in multivarietal brands. Failure

Table 4. Data from aroma, juiciness and overall liking from sensorial evaluation and data from predicted fuzzy model 1 of apricot samples Lady cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) from Year 1 and Year 2.

Tabla 4. Datos de aroma, jugosidad y gusto general de la evaluación sensorial y datos del modelo 1 difuso pronosticado para muestras de albaricoques Lady Cot (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) del año 1 y del año 2.

| Samples | Aroma | Juiciness | Real data overall liking | Predicted data fuzzy model |
|---|---|---|---|---|
| LC_1_Year 1 | 4,25 | 3,05 | 3,50 | 4,05 |
| LC_2_Year 1 | 3,15 | 3,80 | 3,40 | 3,59 |
| FR_1_Year 1 | 4,00 | 5,25 | 4,60 | 5,00 |
| FR_2_Year 1 | 4,05 | 5,25 | 4,20 | 5,00 |
| FB_1_Year 1 | 2,71 | 2,71 | 2,79 | 2,38 |
| FB_2_Year 1 | 2,60 | 2,70 | 2,60 | 2,38 |
| LC_1_Year 2 | 4,15 | 3,90 | 3,35 | 4,05 |
| LC_2_Year 2 | 4,15 | 3,90 | 3,34 | 4,05 |
| FR_1_Year 2 | 3,65 | 4,10 | 4,10 | 3,70 |
| FR_2_Year 2 | 4,50 | 5,06 | 3,29 | 5,00 |
| FB_1_Year 2 | 4,00 | 3,19 | 3,64 | 4,05 |
| FB_2_Year 2 | 3,50 | 3,00 | 3,35 | 3,59 |

Table 5. Data from hardness, aroma, juiciness and overall liking from sensorial evaluation and data from predicted fuzzy model 2 of apricot samples Lady cot (LC_1 and LC_2), Faralia (FR_1 and FR_2) and Farbaly (FB_1 and FB_2) from Year 1 and Year 2.

Tabla 5. Datos de dureza, aroma, jugosidad y gusto general de la evaluación sensorial y datos del modelo difuso predicho 2 de muestras de albaricoques Cuna Lady (LC_1 y LC_2), Faralia (FR_1 y FR_2) y Farbaly (FB_1 y FB_2) de año 1 y año 2.

| Samples | Hardness | Aroma | Juiciness | Real data overall liking | Predicted data fuzzy model 2 |
|---|---|---|---|---|---|
| LC_1_Year 1 | 7,15 | 4,25 | 3,05 | 3,50 | 3,62 |
| LC_2_Year 1 | 6,50 | 3,15 | 3,80 | 3,40 | 3,59 |
| FR_1_Year 1 | 4,70 | 4,00 | 5,25 | 4,60 | 5 |
| FR_2_Year 1 | 5,20 | 4,05 | 5,25 | 4,20 | 5 |
| FB_1_Year 1 | 4,71 | 2,71 | 2,71 | 2,79 | 2,37 |
| FB_2_Year 1 | 3,35 | 2,60 | 2,70 | 2,60 | 3,16 |
| LC_1_Year 2 | 7,30 | 4,15 | 3,90 | 3,35 | 3,62 |
| LC_2_Year 2 | 7,25 | 4,15 | 3,90 | 3,34 | 3,62 |
| FR_1_Year 2 | 7,20 | 3,65 | 4,10 | 4,10 | 3,59 |
| FR_2_Year 2 | 6,68 | 4,50 | 5,06 | 3,29 | 4,42 |
| FB_1_Year 2 | 3,87 | 4,00 | 3,19 | 3,64 | 4,05 |
| FB_2_Year 2 | 5,40 | 3,50 | 3,00 | 3,35 | 3,59 |

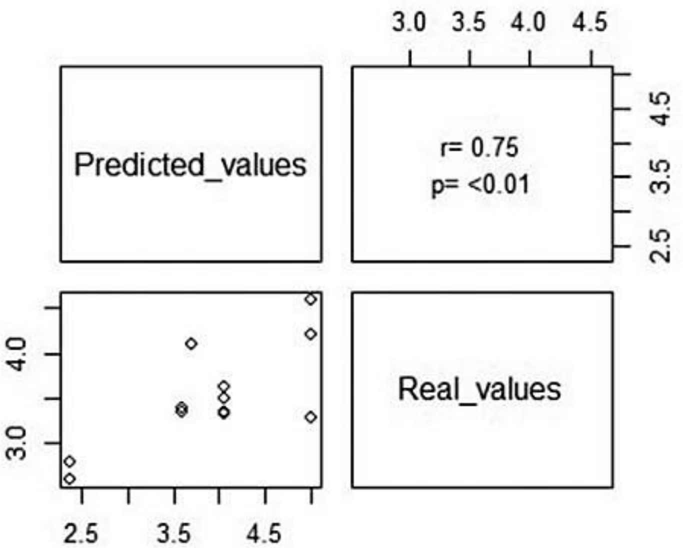


Figure 9. Scatterplot with Pearson coefficient and p-value of correlation analysis of predicted values from fuzzy model 1 and Real_ values (overall liking scores) from sensorial evaluation of all samples.

Figura 9. Diagrama de dispersión empleando el coeficiente de Pearson y valor p del análisis de correlación de los valores pronosticados para el modelo 1 difuso y los valores reales (puntajes generales de agrado) de la evaluación sensorial de todas las muestras.

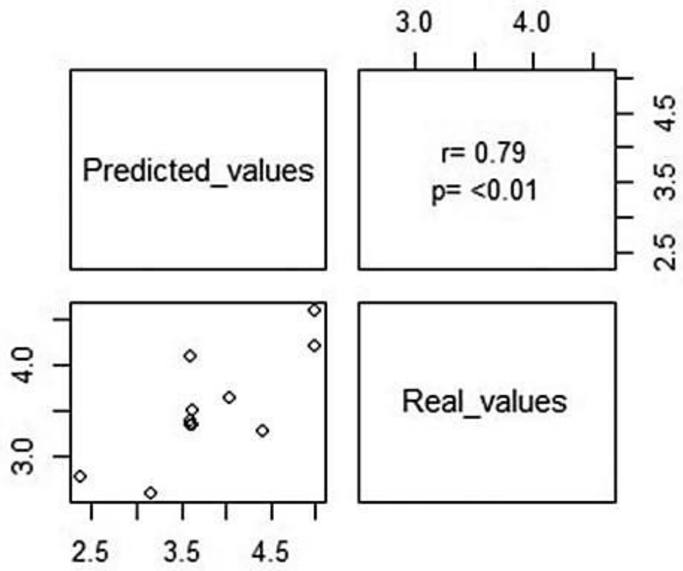


**Figure 10.** Scatterplot with Pearson coefficient and p-value of correlation analysis of predicted values from fuzzy model 2 and Real_ values (overall liking scores) from sensorial evaluation of all samples.

**Figura 10.** Diagrama de dispersión empleando el coeficiente de Pearson y valor p del análisis de correlación de los valores pronosticados para el modelo 2 difuso y los valores reales (puntajes generales de agrado) de la evaluación sensorial de todas las muestras.

in quality stability was successfully demonstrated by univariate and multivariate analyses. Univariate analysis showed significant differences, especially for what concerns textural properties and aroma, while MFA analysis demonstrated an overall significant difference among Lady cot and late varieties Faralia and Farbaly. New quality indexes such as COL and CI parameters, as well as sensory attributes related to texture, were better related to overall liking. The Multiple Factor Analysis was efficient in interpreting relationships among almost all variables, although it is suggested that relation between mealiness and overall liking was not highlighted due to the existence of non-linearity relationship among those variables. Use of expert knowledge mixed with information from sample data enabled development of Linguistic variables and rules of two different fuzzy models. Correlation studies between real and predicted data showed a higher $R^2$ coefficient, especially for fuzzy model 2. MRL1 did not comply with regression assumptions while MRL2 was not significant. Therefore, the fuzzy model might be a valuable tool to evaluate non-linear and small data from fruit sensorial studies if expert-knowledge is available. Moreover, the possibility to describe different relations by setting specific rules for each input parameter enables the use of the fuzzy model in complex situations. It is model-free by nature and it allows a certain degree of uncertainty, which may properly reproduce the way humans can think. For what concerns apricot brand quality, it is suggested that results of the sensory analysis might be extended also to the consumer level. Additionally, the use of proper ordination analysis is needed in order to highlight the non-linearity of data that possibly exists among quality parameters and overall liking.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## Acknowledgments

We would like to thank all professionals and operators of Sata srl who actively participated in the research project.

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# 5- A New Sensory Approach Combined with a Text-Mining Tool to Create a Sensory Lexicon and Profile of Monovarietal Apple Juices

This chapter is dedicated to the article publication:

Mendes da Silva, T., Marinoni, D. T., Peano, C., & Giuggioli, N. R. (2019). A new sensory approach combined with a text-mining tool to create a sensory lexicon and profile of monovarietal apple juices. Foods, 8(12). https://doi.org/10.3390/foods8120608 foods

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Article

# A New Sensory Approach Combined with a Text-Mining Tool to Create a Sensory Lexicon and Profile of Monovarietal Apple Juices

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Received: 10 October 2019; Accepted: 19 November 2019; Published: 22 November 2019

**Abstract:** Single-cultivar juices may be a valuable way to introduce different versions of a product to the market and obtain price discrimination. To communicate a product's value, complex characteristics incorporated by each cultivar must be identified. New sensory methods rely on the assessor's ability to recall attributes; however, the use of objective vocabularies may improve the sensory profiling. This work aimed to profile monovarietal apple juices by using projective mapping (PM) combined with ultra-flash profiling (UFP) supported by a sensory wheel built with a text-mining tool. Samples were also analyzed for physicochemical parameters to provide more information to the assessment. The assessor coordinates from PM were used in multiple factor analysis with confidence ellipses to assess differences among samples. A goodness-of-fit test was applied to select the most meaningful descriptors generated through the UFP test by calculating the expected frequency of choosing a descriptor from the sensory wheel and comparing it with the observed values. The methodology provided a more accurate sensory profile compared to previous research on fresh apples and juices. Elstar, Jonagold, and Pinova were considered as sweet juices, and Gravensteiner was described as sour and astringent, with green-apple notes. Rubinette was described as having a strong taste and cloudy aspect.

**Keywords:** sensory; fruit; projective mapping; quality; apple juice; text mining; sensory wheel

## 1. Introduction

Increase of competitiveness in the internationalized juice market encourages European producers to develop strategies to create value [1] and differentiate their products [2]. Among all marketing strategies, product variation is key to segmenting consumer demand and obtaining price discrimination in the market [3]. It is well-known that different product versions may help to highlight a producer brand from those of others, and consumers may be less resistant to higher prices compared to the standard version of the same product [3]. In the case of the juice market, there is already a wide range of alternatives to purchase from, which leads to differences in loyalty levels in a brand [1].

In the apple juice market, use of local apple cultivars may be a valuable way to introduce product variation and to create a unique profile that is linked to a specific production context, thus creating quality attributes and promoting emotional meaning among consumers [2,4]. In monovarietal juices, typical features of particular cultivars, such as sweetness and aromatic notes, are usually marketed with the product [5]. Therefore, it is essential that complex sensory characteristics incorporated by each cultivar are identified and eventually communicated, because the degree of information available to consumers determines the value associated to the product [2].

There has been an intense development of sensory methodologies for mapping and profiling complex products that are known to be efficient alternatives to conventional methods (such as check-all-that apply and projective mapping), without requiring extensive training of assessors [6]. Many of these methods rely on the assessor's ability to recall specific attributes to profile the product [7]. However, there is great evidence that the use of objective vocabularies in different sectors (industries or research departments) has led to a consistent improvement of product descriptions [8]. Objective vocabularies ensure better agreement among panelists since communication is made using the same reference [8]. In the case of apple juice, many authors have already developed a comprehensive lexicon for describing complex sensory attributes, although this information has not yet been exploited for further single-cultivar product characterization. Furthermore, no systematic way has been proposed to put together information from the literature to create a common lexicon for apple juice products. Among different automatic approaches, data mining is becoming a promising multidisciplinary field that involves informatics, statistics, and pattern recognition. One of its current aims is to analyze large amounts of data to find meaningful and useful information from the market, and to use it to identify new consumption trends. Among all methods involving data analysis, the text-mining process is an emerging technique that focuses on splitting and organizing a text into terms in order to analyze the most and least frequently used words and their associations. To the best of our knowledge, this tool has not yet been used at the level of sensory data, to improve a product's characterization.

Thus, the aims of this work were twofold: to use emerging sensory methods to describe complex characteristics of six monovarietal apple juices and to build an apple sensory wheel to be used as a reference lexicon through a text-mining tool. Samples were also analyzed for physicochemical (total soluble content, titratable acidity, and dry matter) and colorimetric parameters with a chromameter, in order to improve quality information while relating it to the sensory attributes.

## 2. Materials and Methods

### *2.1. Physicochemical Parameters and Colorimetric Analysis*

The six monovarietal apple juices from apples grown in south Tyrol and branded Kohl—Pinova, Gravensteiner, Rouge, Jonagold, Elstar, and Rubinette—were acquired from a Northern Italian local market. Total solid soluble (TSS), titratable acidity (TA), and colorimetric parameters were determined in triplicate from juice samples. TSS was measured with a digital refractometer (Atago, mod. PAL-1) and is expressed in percentage form, while TA was assessed by titration with 0.1 N NaOH to pH 8.1 and is expressed as g/100 g of malic acid. The ratio of TSS and TA (Ratio TSS/TA) was calculated, as well as the BrimA index, as proposed by others [9], for apple fruit. The BrimA index, which stands for "°Brix minus Acidity" is calculated using the following formula:

$$\text{BrimA} = \text{Total soluble solids} - (k \times \text{Titratable acidity}) \quad (1)$$

where $k$ is a constant that may vary between fruit species/cultivars due to differing mixes of acids and sugars [10]. As suggested in previous research, the coefficient for apples is 10.

Dry matter (DM) was determined gravimetrically by heating all samples in a water bath at 100 °C for 4 h, in order to avoid boiling and water splashing, followed by drying the samples at 70 °C in the oven for 24 h. Samples were subsequently cooled in a desiccator, in order to be weighed at room temperature. The procedure was repeated until a constant weight was reached.

Results are expressed in percentage terms as follow:

$$[(C - A) / (B - A)] \times 100 \quad (2)$$

where $A$ = weight of Petri dish; $B$ = total weight of fresh sample + Petri dish; and $C$ = total weight of dry sample + Petri dish.

The color of juice samples was measured with a handheld colorimeter (Konica Minolta, mod. CR-400). The parameters L*, a*, and b* were recorded with Konica Minolta software (SpectraMagic

NX software). Derived from L*, a*, and b*, other color indexes previously tested were calculated in order to enhance sensitivity of color evaluation [11] as follows:

$$\text{Chroma } (C^*)\text{: } \sqrt{a^2 * + b^2 *} \tag{3}$$

$$\text{Hue angle } (h^*)\text{: } tan^{-1}\frac{b*}{a*} \tag{4}$$

The h* is a qualitative parameter of colorfulness since it reflects the visual color appearance with reference to a gray color with the same lightness. In the case of apple juice, it becomes redder when the hue decreases and yellowish when h* increases. The C* parameter is a quantitative parameter and is related with the color intensity or saturation since it expresses the degree of difference of a hue in comparison with a gray color with the same lightness [12].

### *2.2. The Text-Mining Tool and the Wheel Development*

A list of descriptors was developed with a text-mining process, using the R package "tm" [13]. The "Material and Methods" and "Results and Discussion" sections of 17 peer-reviewed papers [2,5,8,14–27] related to sensory analysis of apple juice from 1998 to 2018 were selected from the Scopus database to be the "corpus" of the text-mining computation. Before texts could be assessed, a preprocessing step was necessary to reduce the amount of useless information of the corpus and transform the text into "tokens" (units of text such as words). This was required because full texts are too specific to perform meaningful computations [28]. In this work, this process was computed automatically to remove numbers, common words, capitalization, "stop words", and punctuation. After the preprocessing step, the corpus was transformed to a document term matrix (dtm), a structured matrix with frequencies of terms where each row represents a document (uploaded articles) and each column represents a term. The dtm contained more than 1500 terms that appeared at least once, leading to a very high value of sparsity (>90%). This means that the dtm presented many empty cells, which is very common in a text-analysis process [13]. Therefore, terms that were not present in at least 10% of the documents were removed. This operation gave rise to a dtm composed of only 91 terms.

Filtering and normalization were also needed to further clean the corpus, select meaningful data, and to fuse words with identical meaning. It is important to note that those steps were mainly done manually, since text-mining tools do not take into consideration the meaning of the words, and efficiency of cleaning may eventually present some flaws, such as unremoved punctuation. Figure 1 demonstrates the network of the most frequent terms based on their co-occurrence in the selected articles prior to the manual filtering and the normalization step. It is evident that punctuation was not completely removed from the corpus.

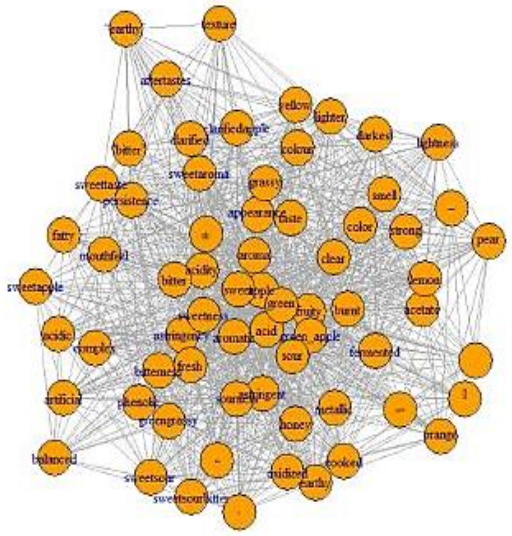


**Figure 1.** Network of most frequent terms based on their co-occurrence in the selected articles before the manual filtering and the normalization step.

Filtering and normalization are also considered critical because they can strongly influence the subsequent analysis, as they define the semantics of the texts [28]. Some authors may suggest to stem the text, a process called "lemmatization", where a rule-based algorithm will convert inflected forms of words to their most essential meaning [28] so they can be recognized by computer (e.g., sour, sourness, and sourest to sour*). However, this process may sometimes be problematic, depending on the type of word (e.g., flowery to flow*) and, thus, in this work, it was not applied. In this work, expert knowledge from SATA S.r.l. and University of Turin was applied to filter and normalize the terms, avoiding loss of information and inclusion of bias. Furthermore, only descriptive data were selected, and affective data were not considered. Finally, this process also included the combination of occurring token pairs of tuples (e.g., green-apple), as suggested by other authors [29]. The normalization process provided a reduction from 91 to only 53 terms. Additional terms were introduced in order to complete the wheel information and properly organize the attributes.

### *2.3. Sensorial Analysis*

Fifteen panelists—eight female and seven male—ranging from 22 to 35 years old, from SATA S.r.l. (Alessandria, Italy), with previous experience in sensory evaluation of fresh fruit were subjected to further theoretical training by discussing the definition of quality parameters concerning taste, texture, odor, and aromatic notes that were present in the developed sensory wheel. A quantity of 50 mL of each juice sample was codified with a 3-digit code and presented simultaneously, in random order, for each assessor. Assessors were asked to place each juice on a 60 × 40 cm sheet based on their similarities or differences. Individually, they were then asked to add from at least one to a maximum of five descriptors from the sensory wheel to each sample placed on the map, as a means to describe the sensory characteristics, following the projective mapping combined with the ultra-flash profile (PM-UFP) methodology [2]. For each sample, both X and Y coordinates were collected and compiled in a table, as described by Stolzenbach [2], along with the generated descriptors.

### *2.4. Statistical Analysis*

Results from physicochemical and colorimetric data were analyzed with one-way analysis of variance (ANOVA), while results from sensorial analysis were analyzed with the multivariate multiple factor analysis for contingency tables (MFACT). The coordinates X and Y from each assessor of each product were treated as a group of two active variables to build the first two dimensions. Data were not scaled. Furthermore, 95% confidence ellipses were applied around the sample mean points, letting the bootstrap sequence iterate on the assessor's partial (rotated) coordinates instead of the original assessor data, as suggested by other authors [30]. Using this approach, the confidence intervals do not include the assessor's variability, since the objective is to compare the apple juice products.

The frequencies of terms to be used as supplementary variables in the MFA analysis following the UFP method were selected based on the common practice of choosing a descriptor that is cited no less than an arbitrary number of times by the panelists (classic approach) [2]; in this work, this was at least three times. In order to further emphasize the consensus and to determine when a particular descriptor was significantly selected to describe each single-cultivar juice sample, the goodness-of-fit test was used to assess how the observed frequency values for each sample were significantly different from the expected frequency values, where the expected frequency was considered to be the number of times a descriptor would be selected from random chance.

Considering the possibility of choosing "d" attributes that comprise the sensory wheel, and the possibility of choosing from one to five attributes for each sample, for each assessor, the expected frequency E was calculated as follows:

$$\mathrm{E} = P \times \text{number of judges} \quad (5)$$

where $P$ is the probability that a descriptor is chosen from the sensory wheel by an assessor, calculated as the following:

$$P = \frac{C}{TC} \quad (6)$$

where $TC$ is the number of possible combinations to select from 1 to n descriptors; and $C$ is the number of possible combinations to select 1 specific descriptor from 1 to n descriptors. Therefore, $TC$ and $C$ were calculated as follows:

$$TC = \frac{d!}{1! \times (d-1)!} + \frac{d!}{2! \times (d-2)!} + \frac{d!}{3! \times (d-3)!} + \frac{d!}{4! \times (d-4)!} + \ldots + \frac{d!}{n! \times (d-n)!} \quad (7)$$

$$C = \frac{(d-1)!}{1! \times (d-1-1)!} + \frac{(d-1)!}{2! \times (d-1-2)!} + \frac{(d-1)!}{3! \times (d-1-3)!} + \frac{(d-1)!}{4! \times (d-1-4)!} + \ldots + \frac{(d-1)!}{n! \times (d-1-n)!} \quad (8)$$

## 3. Results and Discussion

### *3.1. Physicochemical Parameters and Colorimetric Analysis*

In Figure 2, it is possible to observe that the Rubinette juice was the sample with the highest level of TSS, while Gravensteiner had the lowest value. Pinova, Jonagold, Rouge, and Elstar presented intermediate values. The Rubinette sample also presented the highest value of TA, along with the Rouge juice, while there were no significant differences among the other juice samples, considering a confident interval of 95% level. Results of dry matter were consistent with TSS values for all samples (Figure S1).

It is well-known that differences in TSS alone do not have practical importance regarding consumer perception of fruit sweetness. Thus, it is very common to use the TSS/TA ratio to obtain better predictions of sweetness [10]. Apple fruit with TSS/TA ratios over 20 are considered to be sweet, while values under 20 are considered to be sour [9]. In this work, the values obtained for both TSS/TA ratio and BrimA reflect the sensory profile described in different articles [30–32]; that is, Jonagold, Pinova, and Elstar were ranked as the sweetest samples, while Gravensteiner, Rubinette, and Rouge were the least sweet. It is interesting to observe in Table 1 that values of the TSS/TA ratio and BrimA did not rank all samples in the same order. This might be due to BrimA's characteristics of reducing the impact of acidity values in the final index value compared to TSS/TA ratio by only subtracting TA from TSS instead of dividing. This approach might be reasonable considering that small changes in acidity values lead to higher changes in taste perception compared to sweetness [33].

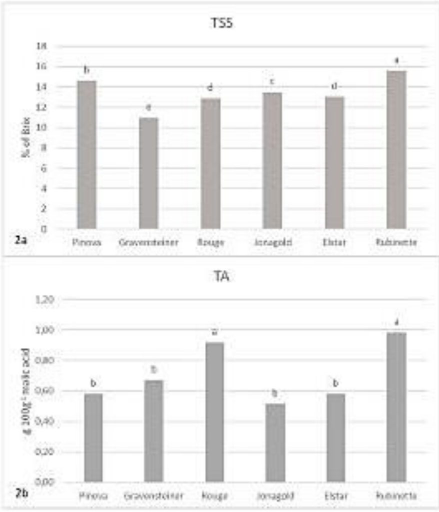


**Figure 2.** Total soluble solids (TSS) (**2a**) and Titratable acidity (TA) (**2b**) values of apple juice samples. Different lower-case letters (a–d) show significant differences among treatments ($p$-value ≤ 0.05).

**Table 1.** Ratio total soluble solids/titratable acidity and BrimA values of apple juice samples and their relative rank, in descending order.

| | Ratio TSS/TA | Rank | BrimA | Rank |
|---|---|---|---|---|
| Pinova | 25.1 | 2 | 8.8 | 1 |
| Gravensteiner | 16.4 | 4 | 4.3 | 5 |
| Rouge | 14.1 | 6 | 3.7 | 6 |
| Jonagold | 26.2 | 1 | 8.3 | 2 |
| Elstar | 22.5 | 3 | 7.2 | 3 |
| Rubinette | 15.9 | 5 | 5.8 | 4 |

The TSS/TA ratio ranks the Jonagold sample as the sweetest, while BrimA indicates the Pinova sample. The same occurs for Gravensteiner and Rubinette samples, in which Gravensteiner would be considered less sweet than Rubinette, considering the TSS/TA ratio, while the opposite is true for the BrimA index. In this work, the BrimA index was introduced in order to properly evaluate the relationship between TSS and TA. This index takes into account differences in ratios of acids and sugars in different species by introducing a k-coefficient [33]. The main idea is that the human tongue perceives sugar and acids with differing sensitivities; thus, this index allows smaller amounts of acid to make the same numerical change to BrimA, as well as sugar [33–35]. Although different articles describe the sensory profile of the fresh-apple samples used in this work [36–38], no information is available regarding comparisons among Rubinette, Gravensteiner, Pinova, and Jonagold sweetness perceptions. Therefore, the use of the sensory analysis is the only possible way to verify if one of the two parameters is the best approximation of sweetness perception as a quality indicator.

Concerning the colorimetric assessment, in Figure 3, it is suggested that Jonagold has presented a distinct color concerning the degree of yellowness of the juice (demonstrated by higher values of b), and a more intense color compared to the other samples (demonstrated by higher values of C*).

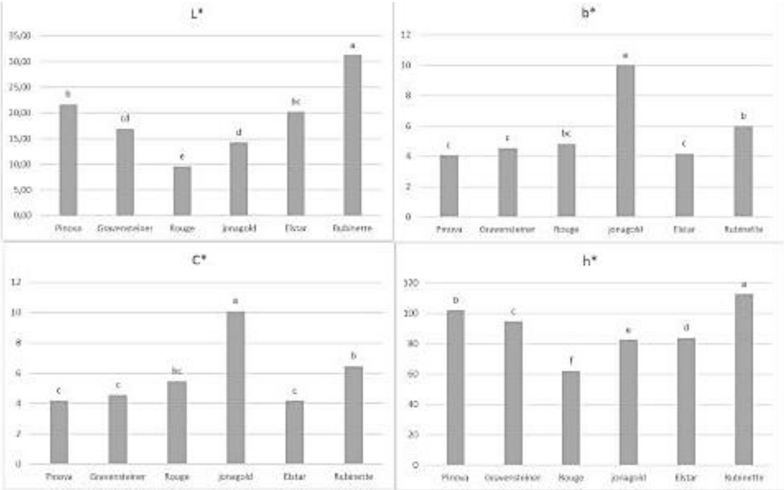

**Figure 3.** L*, b*, Chroma (C*), and hue angle (h*) As stated in the previous literature [35], the lower levels of anthocyanins of Pinova juice contribute to a less-red color and a lighter appearance of the sample. Thus, in this assessment, the level of anthocyanins of the Pinova sample could have contributed to its more yellowish color compared to the Jonagold juice, as indicated by the h* index measured in this work.

By observing a* values (Figure 4), however, it is clear that Jonagold also presented a redder color, along with the Rouge sample. This probably affected the h* value which, by taking account of both a* and b* values, identifies Rubinette and Pinova as the yellowish-greenish samples, while Rouge and Jonagold were redder. Pinova and Rubinette also presented a brighter or lighter color compared with the same two samples, as suggested by L* values.

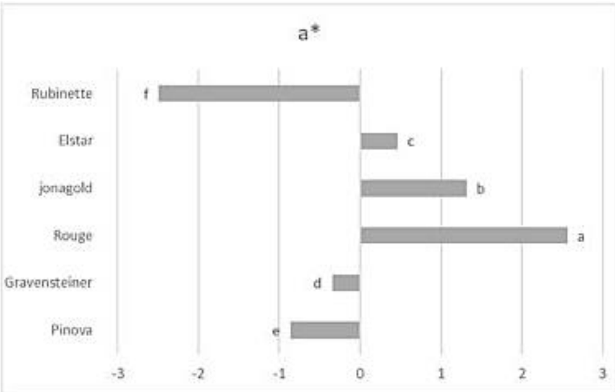


**Figure 4.** The a* values of apple juice samples. Different lower-case letters (a–f) show significant differences among treatments ($p \leq 0.05$).

Assessing the complex index h*, along with the classic colorimetric values, enables the detection of different color patterns behind the term "lighter", which were previously used indistinctly for both Jonagold and Pinova juices in other authors' work [4]. As stated in the previous literature [35], the lower levels of anthocyanins of Pinova juice contribute to a less-red color and a lighter appearance of the sample. Thus, in this assessment, the level of anthocyanins of the Pinova sample could have

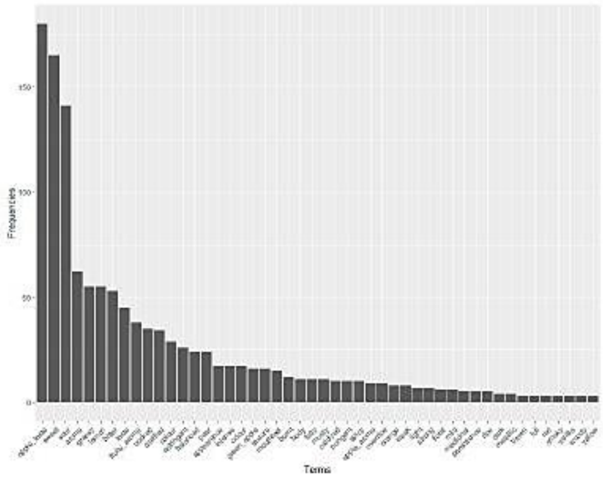


**Figure 5.** Frequency of the selected terms obtained from the text mining and normalization process.

Based on Figure 5, it is evident that apple taste, sweet, and sour are the most cited terms and the most important in describing apple juice. The text-mining tool also provided many attributes that are described as negative notes (such as medicinal, musty, smoky, and burnt), possibly from microbiological spoilage or technological issues during apple juice processing [24,39]. Therefore, considering the least-cited words is also important, in order to retain valuable information from the corpus. In this work, it is demonstrated how the text analysis can compile valuable data from the source; however, expert knowledge is still a fundamental resource to build an exhaustive system of information based on the available data. The sensory wheel is shown in Figure 6.


**Figure 6.** Sensory wheel developed with sensory attributes selected from the text-mining process.

The resulted sensory wheel included the most- and least-cited terms in the selected bibliography, in order to cover all macro aspects (divided by different colors in the wheel) of apple juice quality. This process also included complex attributes, such as texture, which might be assessed through tactile sensations in the mouth or visually, based on the product's appearance, as is demonstrated in Figure 6. Taste, which is the most cited macro attribute, includes qualitative (bitter, sour, and sweet) and quantitative (intensity and persistence) attributes. Usually, those descriptors are not present in conventional sensory methods, such as quantitative descriptive analysis (QDA) [6,7]. It was decided to retain this information in the assessment due to the relevance of these attributes in taste perception. To conclude, considering the use of assessors that have undergone theoretical training, astringent, metallic, and pungent were placed in the mouthfeel group, while apple taste was included under the odor and aromatic notes group, split into green- or ripe-apple attributes. However, it is important to note that this organization might be misleading in the context of a sensory evaluation at the consumer level, due to lack of knowledge concerning the meaning and the classification of sensorial terms.

### 3.3. Projective Mapping (PM) and Ultra-Flash Profile (UFP) Characterization

The PM method led to an acceptable differentiation of juice samples, as shown by the higher values of total explained variance (84.12%) in the first two dimensions Dim 1 and Dim 2 (Figure 7).

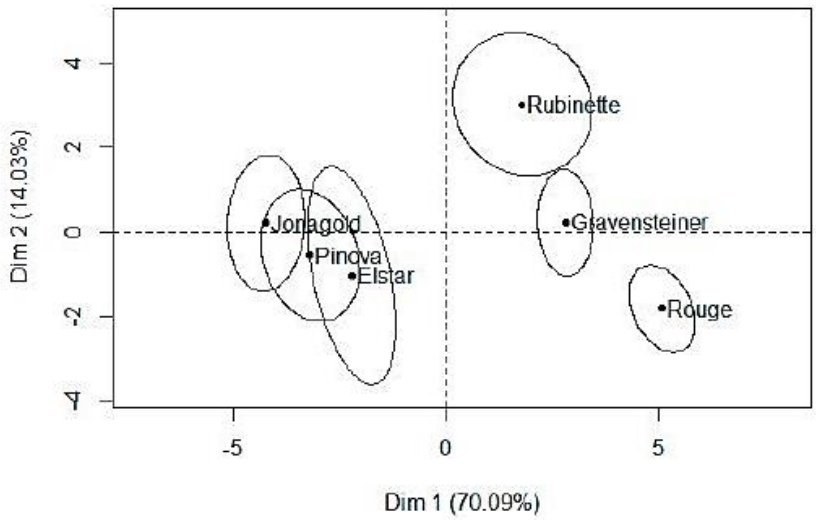


**Figure 7.** Dimension 1 (Dim 1) and Dimension 2 (Dim 2) of the multiple factor analysis individual plot of apple juice samples and confidence ellipses.

The higher percentage of explained variance (70.09%) of dimension 1 highlights the higher level of agreement among assessors in sample discrimination. Considering the rank obtained by the TSS/TA ratio and BrimA in Table 1, assessors distinguished two groups of samples, probably based on these parameters' values over the first dimension. In fact, samples with higher values of TSS/TA ratio and BrimA are positioned on the right side of the individual plot, while samples with lower values are on the left side. Assessors were more prone to discriminate samples through the second dimension only in the case of juices with higher levels of TA.

In order to conduct the ultra-flash profile test, assessors were asked to choose from one to five samples of the sensory wheels. Assessors were also instructed to use the descriptors present on the outer ring of the wheel and, for the case of the group odor and aroma notes only, they were allowed to use the generic subcategories vegetable, fruity, toasted, and spicy. Therefore, following the calculations proposed in Equations (5)–(8), the possibility of choosing 46 different attributes from the sensory wheel led to the probability of choosing a particular descriptor by each assessor of 10% (Figure 8) and a rounded expected frequency, E, of two citations by descriptor by juice sample, considering all 15 assessors. As suggested in the literature, considering the low value of the expected frequency, the binomial test was used instead of the chi-squared test, to assess goodness-of-fit [40]. By assessing the *p*-values obtained using increasing values of frequency, the test suggests it is sufficient to have more than four citations for an attribute for a specific juice sample in order to consider it was not chosen by chance on the product description.

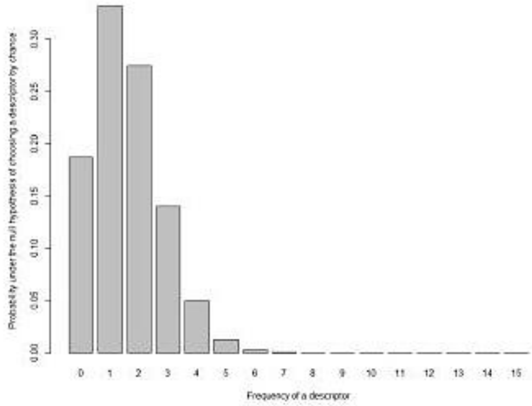


**Figure 8.** The expected probability distribution for the binomial with 15 trials (number of assessors) considering the probability of 10% of choosing a descriptor from the developed sensory wheel.

As is demonstrated in Figure 9, the amount of information retained with the classical approach is higher than the number of descriptors validated with the goodness of fit approach (Figure 10), and also includes negative descriptors of apple juice samples, especially in regard to the Rouge sample. However, there is a lack of coherence in the disposition of some descriptors. For example, the descriptor "bodied" is positioned in contrast with the descriptor "cloudy", even though it is commonly accepted that cloudy apple juices are usually perceived as bodied [41], and "grassy" is close to samples described as "sweet" and far from those described as having a green-apple note, which is in contrast to the results of previous work concerning the aroma profile of apples using sensorial and chemical analyses [21,42]. Moreover, the distribution of descriptors in the MFA plot is not sufficiently spread to describe samples in a more specific way. The use of different scales between the active (coordinates) and the supplementary (frequencies) variables, and the low frequency of citations, led to a poor distribution of the descriptors compared to the samples in the multivariate space. Therefore, the selection of descriptors with the goodness-of-fit approach highlighted in Figure 10 is clearer and more coherent with the information available in the literature concerning fresh and juice samples of the cultivars used in this study.

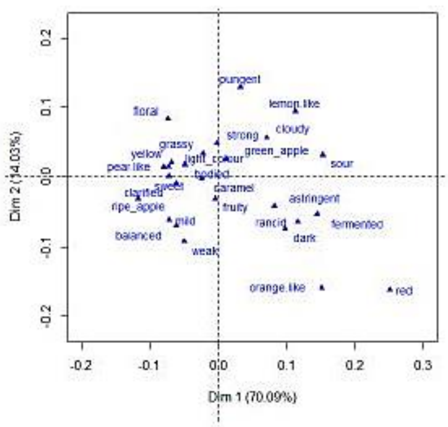


**Figure 9.** Multiple factor analysis plot of descriptors selected through the classic approach.

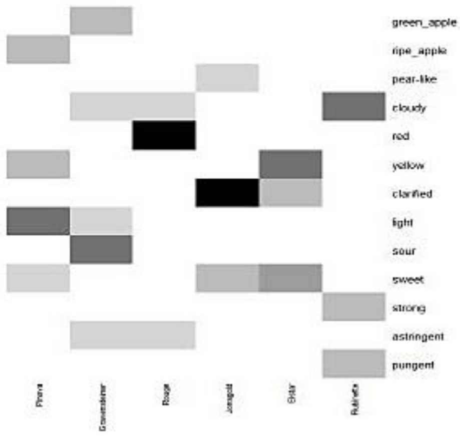


**Figure 10.** Heatmap of $p$-values < 0.05 obtained for each product and each descriptor from the binomial test. Darker colors indicate lower $p$-values (<0.000001), and lighter gray colors indicate higher $p$-values (<0.01).

The $p$-values obtained in the binomial tests suggest that Elstar, Jonagold, and Pinova were considered to be significantly sweet. Elstar presented the lowest $p$-value among all samples, indicating a higher number of citations on sweetness, suggesting that the aromatic profile of this cultivar [5] led to an increased perception of sweetness, despite intermediate values of this sample with regard to brix and both TSS/TA ratio and BrimA index. Jonagold presented a lower $p$-value compared to Pinova, which is more in agreement with the rank obtained with the TSS/TA ratio compared to the BrimA index, meaning that this parameter is a better approximation of sweetness perception. Therefore, this work confirms that the BrimA index in the case of apples may not improve the prediction of the sweetness perception over the TSS/TA ratio, as was suggested in previous work [10].

The sour attribute was significantly chosen only to describe the Gravensteiner sample, even though the TSS/TA ratio also indicated the samples Rubinette and Rouge as sour (values <20) samples. The values of the TSS/TA ratio of the three samples obtained in this work were similar, regardless if they were derived from higher concentrations of TSS and TA, as in the cases of Rubinette and Rouge, or lower concentrations of TSS and TA, as for Gravensteiner juice. This is a major drawback of the use of this parameter. Apparently, the higher amount of TSS present in Rouge and Rubinette samples was sufficient to contrast the sour taste induced by the higher concentration of TA, while the lower levels of TSS and TA of Gravensteiner led to taste discrimination in terms of sourness. If confirmed, at a consumer level, that this information is very important for the development of apple juice for specific segments of consumers that prefer a sour taste. Interestingly, regarding other taste attributes, the Rubinette sample was described as presenting a strong taste, which could be related to the higher proportions of TSS and TA values.

Concerning the apple juices' appearance, the results obtained from the colorimetric assessment were partially comparable to the sensory assessment. Gravensteiner and Pinova were considered to present a lighter color, while, in regard to the colorimetric parameter $L^*$, this is true also for Rubinette samples. Pinova and Elstar were considered to be the most yellowish, while the $h^*$ index also indicated the Rubinette juice. The higher level of cloudiness present in the Rubinette juice, demonstrated by the lower $p$-value with respect to the other samples, could have led to differences in the colorimetric measurements, since the colorimeter is only able to assess the color of samples through the reflectance modality [10]. The same may be applied to the Jonagold juice, which presented the second lowest value of $L^*$ and is considered to be the least cloudy sample, along with Elstar. Overall, some of the colorimetric values of samples classified as clarified were underestimated, while those of cloudy samples were overestimated. This has been shown in other work [5], as well. Thus, the introduction of different appearance attributes in the sensory assessment was important to assess the reliability of the colorimetric measurements done in this work. We suggest the use of a spectrophotometer when measuring liquids, since this also takes into account the opacity of products.

Considering the aromatic profile of the apple juices, the descriptions obtained in this work were reasonably similar to those described in the literature. Gravensteiner, which is known to present higher levels of $\alpha$-farnesene, a compound that is related to herbaceous and green notes [38], was the only sample described with a green-apple note, and this is in agreement with the use of the sour descriptor for the taste profiling. Pinova, which is described as an apple having a fruity aroma [43], was profiled with a ripe-apple note, and Jonagold was described as a sample presenting a pear-like aroma, which is in agreement with the work of Jaros et al. [5,44], where the authors highlight the higher amounts of hexyl-acetate in this variety.

Finally, Rubinette was described as a pungent sample. Pungency in apple is associated with molecules that are both related to fruity (acetaldehyde and butanal) or green (hexenal) notes [45], but there is no available information considering the Rubinette sensory profile in order to confirm the obtained data. Astringency was found only for Gravensteiner and Rouge samples. It is not surprising that the Gravensteiner juice was described as astringent since this variety is characterized by higher values of polyphenols, which are known to be less present in the new varieties and may impart bitterness and astringency to food products [46].

## 4. Conclusions

In this work, the use of a sensory wheel, combined with new sensory profiling methods, projective mapping, and ultra-flash profiling, provided the characterization of six different apple juice samples, by taking into account almost all macro aspects present in previous sensorial works. The exploitation of available data through a text-mining tool process to construct the sensory wheel was successfully achieved, although this process must be complemented by expert knowledge, in order to filter and contextualize data into meaningful information and avoid bias and redundancy. Nonetheless, the goodness-of-fit test applied to the descriptors cited during the ultra-flash profiling provided a coherent selection of attributes for each apple juice sample, which resulted in a clearer description of each sample's sensory profile and less contrast with previous work. This work also presented valuable information about how physicochemical characteristics in terms of acidity, brix, and their interaction may affect taste perception in apple juices. Secondly, we suggest colorimetric measurements still need to be improved in order to predict the perceived hue of juices' color. The presented methodology is effective for future analysis and may be extended to other products where sensory information is available in the literature. Furthermore, we highlight that theoretical training concerning the selected attributes to be incorporated in the sensory wheel is fundamental in order to promote proper use, especially in the case of complex attributes, such as texture.

**Supplementary Materials:** The following are available online at www.mdpi.com/xxx/s1, Figure S1: Results of dry matter were consistent with TSS values for all samples.

**Author Contributions:** Conceptualization, D.T.M and C.P; Data curation, T.M.S; Formal analysis, T.M.S; Methodology, T.M.S and N.R.G; Supervision, D.T.M, C.P and N.R.G; Validation, C.P and N.R.G; Writing – original draft, T.M.S.

**Funding:** This research received no external funding

**Acknowledgments:** We would like to thank all professionals and operators of Sata srl who actively participated in the research project and the company Kohl for supplying the samples to the trial.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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# 6- The use of a new explanatory methodology to assess maturity and ripening indices for kiwiberry (Actinidia arguta): Preliminary results.

This chapter is dedicated to the article publication:

Mendes da Silva, T., Briano, R., Peano, C., & Giuggioli, N. R. (2020). The use of a new explanatory methodology to assess maturity and ripening indices for kiwiberry (Actinidia arguta): Preliminary results. Postharvest Biology and Technology, 163. https://doi.org/10.1016/j.postharvbio.2020.111122

Contents lists available at ScienceDirect

Postharvest Biology and Technology

journal homepage: www.elsevier.com/locate/postharvbio

# The use of a new explanatory methodology to assess maturity and ripening indices for kiwiberry (*Actinidia arguta*): Preliminary results

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ARTICLE INFO

*Keywords:*
A. arguta
Harvesting quality
PLS model
MFA model
Colour

ABSTRACT

Harvesting quality is a latent concept that is often summarised by several attributes, which in turn may be described as complex parameters due to their multicomponent structure. Multivariate techniques such as Multiple Factor Analysis (MFA) and Partial least square (PLS) analysis represent suitable tools to investigate quality indices as they are able to compute systems of composite indicators, providing more accurate knowledge than a single attribute. Therefore, the goals of this work are: to describe the evolution of different quality parameters during the harvesting period of new cv Tahi and cv Rua and to analyse their correlations in order to create a model that will highlight new potential harvesting and maturity quality indicators. This will provide knowledge for development of a harvesting index of A. arguta fruit, for which the harvest period is still determined by traditional quality traits. Data from physicochemical, colorimetric and nutraceutical assays were analysed with ANOVA and MFA and fused in a PLS model. We created a PLS model with an $R^2$ value of 0.83 for cv Rua and of 0.44 for cv Tahi. Our results suggest that composite colorimetric parameters may enhance the sensitivity of Hue changes during the harvesting period and are less cultivar-specific than nutraceutical ones. It is suggested that this methodology is applied to larger sample sizes in order to extend the results to the population. Further studies should pay more attention to the use of colorimetric indices and their combination.

## 1. Introduction

The search for harvesting quality traits is a common topic in the scientific literature since it is assumed that fruit composition at harvest is a reliable descriptor of postharvest quality (Nordey et al., 2019). The use of chlorophyll as a harvesting index has become widespread as its content decreases during the ripening of many fruit crops, and it is less susceptible than physico-chemical variables to fluctuations caused by different weather conditions that might occur over the years (Costa et al., 2009; Spadoni et al., 2016; Nordey et al., 2019). In the case of *Actinidia deliciosa* species, in some seasons, soluble solid content (SSC) values evolve slowly in the last period of fruit growth, misleading the definition of fruit ripening evolution (Costa et al., 2009).

*Actinidia* species may display a different behaviour in terms of chlorophyll contents, depending on the cultivar. The green-fleshed kiwifruit of *A. deliciosa* retains chlorophylls in the flesh during ripening, while the yellow-fleshed kiwifruit cultivars are characterised by chlorophyll degradation (Crowhurst et al., 2008), which might occur along with the increase in beta-carotenes, as proposed by Liu et al. (2017). In the case of the red-fleshed kiwifruit, the same authors have stated that the red colour is due to anthocyanin accumulation. Thus, in *Actinidia* species, knowledge of different pigment trends and colour variations during ripening is essential in order to develop harvesting indices.

Different techniques have been proposed to evaluate kiwifruits to define harvesting quality, such as Vis–NIR and NIR spectroscopy in the case of green-fleshed kiwi (e.g. Kiwi-meters®, University of Bologna patent PD2009A000081) (Costa et al., 2009),and colorimetry in the case of yellow-fleshed kiwis (Minchin et al., 2010). Regarding *A. arguta* cultivars, consistent information about chlorophyll or other harvesting indices is lacking (Bok et al., 2017). *Actinidia arguta* displays a short shelf life (1–2 months) if compared to other kiwifruits (Latocha et al., 2014), and determination of harvesting time is the key to guarantee successful storage (Giuggioli et al., 2019) and to market various cultivars. Northern-Italian produce is increasing due to the diffusion of two cultivars, Hortgem Rua® (cv Rua) and Hortgem Tahi® (cv Tahi) (marketed under the Nergi® brand). Both cultivars are marketed under the same brand since they do not differ much externally; however, cv Rua, which is a hybrid between *A. arguta* and *A. melanandra* (Huang, 2016), may develop reddening of the skin or flesh or both when mature and ripe (Hassall et al. (1998)).. For both cultivars, harvest is still determined by traditional quality traits (soluble solid content, firmness

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https://doi.org/10.1016/j.postharvbio.2020.111122
Received 10 June 2019; Received in revised form 7 January 2020; Accepted 12 January 2020
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and dry matter), although fruit classification according to these parameters is time-consuming and analyses are usually carried out on small samples (Costa et al., 2009), which may increase the risk of misleading quality assessment of the batch (Wang et al., 2017).

The use of colorimeters is widespread in fruit quality evaluation because they are portable and allow repeatable measurements (Musacchi and Serra (2018)). In the case of the yellow-fleshed kiwifruit, it was possible to determine a harvesting colour index threshold (hue angle = 104°) for cv *A. chinensis* Hort16A (Minchin et al., 2010), which was later extended for other yellow-fleshed cultivars. Regarding the green-fleshed kiwifruit, minor changes of hue during ripening makes colorimetric assessment of harvesting quality a challenge, and the fruits need to be peeled in order to evaluate the flesh colour. However, colour evaluation in *A. arguta* species is facilitated since the fruit presents an edible peel (Giuggioli et al., 2017), and the colour is a complex parameter that enables the assessment of qualitative (hue) and quantitative parameters such as luminosity and saturation (Pathare et al., 2013).

Overall, harvesting quality is a complex and latent concept that is often summarised by several attributes, which in turn may be described as composite parameters. The challenge of constructing a harvesting quality index by using composite indicators requires the investigation of key indicators and in which ways these indicators can be fused to form a coherent information system (Trinchera et al. (2006)). Thus, multivariate techniques that are able to compute systems of composite indicators, such as Multiple Factor Analysis (MFA) and Partial Least Square (PLS) analysis (Trinchera et al. (2006)), are useful tools to evaluate harvesting at the level of a single variable (e.g. luminosity) and at the global level (e.g. colour). Moreover, fusion of data from complementary parameters can provide "more accurate knowledge and yield better inferences (classifications with lower error rates and predictions with less uncertainty) than a single attribute" (Borràs et al., 2015). Therefore, the goals of this work are as follows: to describe the evolution of different quality parameters during the harvesting period of the new cultivars Tahi and Rua and to analyse their correlations in order to create a model that will highlight new potential harvesting and maturity quality indicators, with the aim to provide information for the development of a harvesting index of *A. arguta* fruit.

## 2. Materials and methods

The cultivars cv Tahi and cv Rua were harvested from an orchard located at Saluzzo (CN), Italy. Vines were trained on T-bar trellises and managed using commercial practices. Four sampling dates of each cultivar were established from August to September when the fruit seeds were entirely black and most of them presented at least 6.5 up to 8 % of SSC values, which are considered the normal index criteria of the industry (Liu et al., 2017). It was decided to harvest fruits within this range according to Latocha et al. (2014), who have defined this range as the best choice for long-term storage under a controlled atmosphere, although fruit that are harvested at a level of 6.5 % might present insufficient aroma and taste (Bok et al., 2017), while other authors have suggested that a different cultivar of *A. arguta* should be harvested at least at 8 % of SSC to achieve high-quality fruits (Fisk et al., 2006, 2008). For each sampling date (expressed as days after bloom-DAFB), entire fruits were collected from two vines and divided into three different size classes, based on weight: 1, 5−10 g; 2, 10−15 g, and 3, > 15 g).. Considering the faster ripening of *A. arguta* compared to *A. deliciosa* fruits (Hassall et al. (1998)), the sampling dates were 80, 90, 100 and 110 DAFB, where rates of physico-chemical changes in *A. arguta* fruit are more evident (Hassall et al. (1998)).

### 2.1. Physico-chemical parameters and colour indices

After the sorting of healthy fruit, soluble solid content (SSC), titratable acidity (TA) content, firmness, dry matter (DM) and colour determined in the juice, obtained by crushing 10 kiwifruit slices with a food processor; measurements were performed in triplicate. The SSC was determined with a digital refractometer (Atago, mod. PAL-1), while TA was measured using an automatic titrator (TRITALABAT 1000 series, Hach) which calculates the volume of NaOH 0.1 N to pH 8.1 of 5 mL of juice diluted in 50 mL of deionised water. Results were expressed as g $kg^{-1}$ of citric acid. Firmness was calculated for 30 replicates using the Texture Analyser TA.XT. PLUS (Stable Micro Systems USA) with a 3-mm penetrometer probe. A puncture test was performed to a 10 % strain, with a pre-test speed of 1 mm $s^{-1}$, a test speed 1 mm $s^{-1}$, a post-test speed of 5 mm $s^{-1}$ and a 5-g trigger force. The DM of 10 replicates was estimated in a disc with a thickness of 10 mm, containing flesh and skin, from the cross section removed from the equatorial region of each fruit. Discs were oven-dried at 65 °C for 24 h and results were expressed in percentages, using the following equation:

$$[(C-A)/(B-A)]\,X\,100$$

- A = weight of Petri dish.
- B = total weight of fresh sample + Petri dish.
- C = total weight of dry sample + Petri dish.

Colour was measured with a colorimeter (Konica Minolta, mod. CR-400) with a D65 illuminant and the 2° standard observer in the equator zone of 200 fruit. In this work, we measured only the fruit skin in order to evaluate the possibility of using the colorimeter as a non-destructive device to assess fruit maturity. Prior to the measurements, the instrument was calibrated with white tiles ($L^* = 93.47$, $a^* = 0.83$, $b^* = 1.33$). The $L^*$, $a^*$ and $b^*$ values were recorded with the Konica Minolta software (SpectraMagic NX software). Deriving from $L^*$, $a^*$ and $b^*$, other colour indices previously tested were calculated in order to enhance the sensitivity of the colour evaluation (Manera et al., 2013; Pathare et al., 2013; Cristina, 2014):

Chroma ($C^*$): $\sqrt{a^{2*}+b^{2*}}$

Hue angle ($h^*$): $\tan^{-1}\frac{b^*}{a^*}$

Mic: $L^*\times a^*/b^*$

H index: $(180-h)/(L^*+C^*)$

A new colour index was also proposed, considering the trend observed in Fisk et al. (2008):

$a^*$ index: $a^*/(L^*+C^*)$

### 2.2. Nutraceutical analysis

All data were expressed on a fresh weight basis. Total polyphenol content (TPC) was determined by the Folin-Ciocalteu method according to Singleton and Rossi (1965), and the antioxidant content (AC) was determined by the Ferric Reducing/Antioxidant Power (FRAP) essay developed by Benzie and Strain (1996). Both analyses included a common prior preparation to obtain sample extracts from 10 g of raw puree obtained from 10 replicates using an extraction solvent. The extraction solvent was prepared with 500 mL of methanol, 1.4 mL of concentrated acid (HCl) and 23.8 mL of deionised water. After 60 min under reduced light conditions, the preparations were homogenised for 15 min to obtain sample extracts.

The TPC was determined by mixing the supernatants of each sample with 30 mL of deionised water and 2.5 mL of Folin-Ciocalteu reagent. After 8 min of incubation, the mixture was spiked with 10 mL of sodium carbonate solution (15 % w/v) and incubated at room temperature (25 °C) for 2 h. Absorbance was measured at 765 nm with a spectrophotometer (UV-1600 PC, VWR), and TPC was expressed as mg $kg^{-1}$ chlorogenic acid equivalents (GAE).

The AC was determined using stock solutions (FRAP) that included 0.3 M acetate buffer (3.1 g sodium acetate, 1 L deionised water and 16 mL acetic acid), 10 mM TPTZ (2, 4, 6-tripyridyl-s-triazine) solution in 40 mM HCl and 20 mM ferric chloride solution. Readings of the co-

595 nm; results were expressed in mol $kg^{-1}$ $Fe^{+2}$.

Total chlorophyll (TCHL) and β-carotene were extracted and quantified according to Nagata and Yamashita (1992).

Ascorbic and dehydroascorbic acid determination was carried out using an Agilent 1200 high-performance liquid chromatograph coupled to an Agilent UV–vis diode array detector (Agilent Technologies, Santa Clara, CA, USA).Extraction was performed according to Donno et al. (2013) with some modifications.

Briefly, 10 g of fresh fruit were homogenised for 30 s in 10 mL of the extraction solution (0.1 M citric acid, 2 mM ethylene diamine tetra-acetic acid (EDTA) disodium salt and 4 mM sodium fluoride in methanol – water 5:95, v/v) on an Ultraturrax (IKA, Dabortechnik, Staufen, Germany). The homogenates were further centrifuged (716 g) for 5 min and then filtered. Subsequently, 10 mL of filtered homogenates were added by 300 μL of HCl 4 N in order to reach a pH of 2.2. Samples were then centrifuged at 6440 g for 5 min at 4 °C and filtered through an activated C18 Sep-Pak cartridge (Waters, Milford, MA). Then, 250 μL of 1,2-phenylenediamine dihydrochloride (OPDA) solution (0,35 g $L^{-1}$) were added to 750 μL of extract. After 37 min in darkness, the samples were analysed via HPLC. For this, 20-μL samples were injected into a reversed-phased Eclipse XDB-C18 (150 × 4.6 mm i.d., 5 μm particle size; Sigma Italiana srl, Ozzano Emilia, Italia). The mobile phase was methanol/water (5/95, v/v), 5 mM cetrimide and 50 mM $KH_2PO_4$ at pH 4.5. The flow rate was kept at 0.054 L $s^{-1}$. The acid ascorbic content (Vit_C) was calculated without considering the dehydroascorbic acid content, and the results were expressed as g $kg^{-1}$.

### 2.3. Statistical analysis

To assess the parameter evolution throughout the four sampling dates, all data (with the exception of Mic, a_index and H_index) were subjected to analysis of variance (ANOVA), using size and sampling date as factors in a two-way ANOVA separately for each cultivar. Special attention was dedicated to significant differences detected throughout sampling dates within the same sample size and the overall trend (the average of samples grouped for sampling date). Averages were separated by Tuckey´s HSD test ($p$-value $< 0.05$).

To determine correlations among parameters, the data were subjected to MFA. Other than provide a common space for samples and variables, that is: a multivariate space defined by factors (dimensions) where each Rua cv and Tahi cv samples and each single parameter is represented, the MFA analysis was used also to demonstrate the relationship between the sets of variables (global attributes or composite indicators) within this common space (Hervé et al., 2013) and as an explanatory technique before building a PLS model. By allowing the introduction of different sets of variables and balancing their influences on the formation of the common space, MFA enriches the assessment, highlighting both the relationships among data at the level of a single parameter (e.g. luminosity represented by parameter L*) and at the level of a global attribute that summarises complementary parameters (e.g. colour represented by all colorimetric parameters). Therefore, MFA, which was performed for each cultivar with the Software R studio (R Core team, 2018), the using "FactoMiner" package (Le et al., 2008), enables the assessment of complex relationships among sets of variables to visually identify which constructs are worth to be used as input for the PLS model, while the relationship among single parameters will define how to build the inner structure of the constructs. Sixteen different parameters were scaled and grouped into new active continuous sets of variables named "colour", "nutraceutical" and "phy.cochemical" in order to group parameters that are complementary among each other and represent a global quality attribute. Two supplementary categorical groups, namely "size" and "harvesting", were added to group samples (observations) respectively by size of fruit and sampling dates to obtain observation centroids. This means that colorimetric, nutraceutical and physicochemical parameters were used to build the common space and to influence the distance among samples, while supplementary groups were only introduced to facilitate the interpretation of the analysis, which, in this work, regards the investigation of the linear relationships of parameters and sets of variables with the harvesting period (represented by the group "harvesting"). A scree plot was produced to decide how many dimensions to keep in the model, and the $p$-values of the parameter's correlation coefficients with the most important dimensions were assessed in order to filter which parameters were better represented in the MFA and potentially important to the PLS model.

Finally, to fulfil the third goal of this assessment, a PLS regression model was built to highlight potential harvesting quality indicators to be used in place of classic parameters (physicochemical). The PLS model is a useful tool to provide a practical summary of how dependent variables are systematically explained by their sets of indicator variables (Trinchera et al. (2006)). It builds a common space bas,ed on dimensions, that explains the maximum common variability of a set of parameters, but differently from MFA, with the constraint of maximising the correlation between one or more sets of parameters (defined as predictors) and a different set of parameters (defined as a dependent construct) (Borràs el al., 2015). Therefore, in this work, the PLS model, built with package "plspm" (Sanchez et al., 2017), was used to provide a quantitative estimation of the relationship between the dependent latent construct harvesting quality trend (named "harvesting _index"), summarised by the physicochemical parameters and sampling dates, and the independent latent constructs named "colour_trend" and "nutraceutical_trend", summarised respectively by colorimetric and nutraceutical parameters. As in the MFA, the purpose of dividing group data into constructs of single parameters is to exploit the possibility of integrating complementary parameters to form global quality attributes to be used as predictors of harvesting quality. Moreover, by creating constructs, the PLS model is robust to multicollinearity of indicators, which is a common pattern among quality data (Haenlein and Kaplan (2004)). Physicochemical data were introduced within the "harvesting_index" construct since it may be seen as a consequence of the proper commercial harvesting period chosen in order to improve storability of the product rather than take part on the formation of the harvesting index. All parameters were introduced as continuous data, except for sampling dates, which were expressed as ordinal data (1°, 2°, 3°, 4°). The choice of the type of constructs (reflective or formative) was a function of the MFA results and considers the presence of correlations among samples, which are required for reflective constructs, while they should be avoided for formative constructs (Andreev et al., 2009; Sanchez, 2013). The selection of single parameters for the model (the manifested variables used as construct indicators) was made based on the MFA results, the PLS selective ratios and a trial and error principle. Data were scaled to account for the fact that the three blocks to be concatenated could have different variances as a consequence of their different measurement types and their unbalanced variable numbers. The centroid was the inner weight scheme type used to compute the average weight of the latent constructs. Cronbach's alpha and Dillon-Goldstein's values were calculated to verify the unidimensionality of the reflective variables, along with loadings and communalities of indicators of the outer model. Path coefficients, $R^2$ and redundancy of inner model were assessed. The bootstrapping procedure was applied to provide $t$-test results for all path coefficients.

## 3. Results and discussion

### 3.1. Physicochemical, colour and nutraceutical analysis

Differences among size were inconsistent in all sampling dates for all parameters analysed, since it was not possible to observe a trend of higher or lower values among sizes. Although, analysis of the overall trend (the average of samples grouped for sampling date) and trend within each sample size was important to assess the data.

The trends of physicochemical parameters differed among cultivars, with the exception of the DM content, which was the parameter with

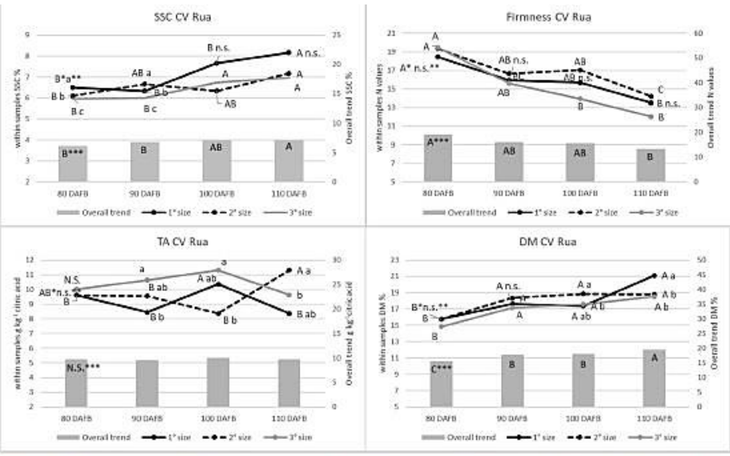


**Fig. 1.** Soluble Solid Content (SSC), firmness, Titratable acidity (TA) and Dry matter (DM) values of the *Actinidia arguta* cultivar Hortgem Rua over time.
*Different capital letters (A–C) show significant differences (*p*-value ≤ 0.05) within treatment. **Different minor letters (a–c) show significant differences among treatments (*p*-value ≤ 0.05) for each harvesting date. *** Different capital letters (A–C) show significant overall (average of samples grouped for sampling date) differences (*p*-value ≤ 0.05) for each harvesting date.

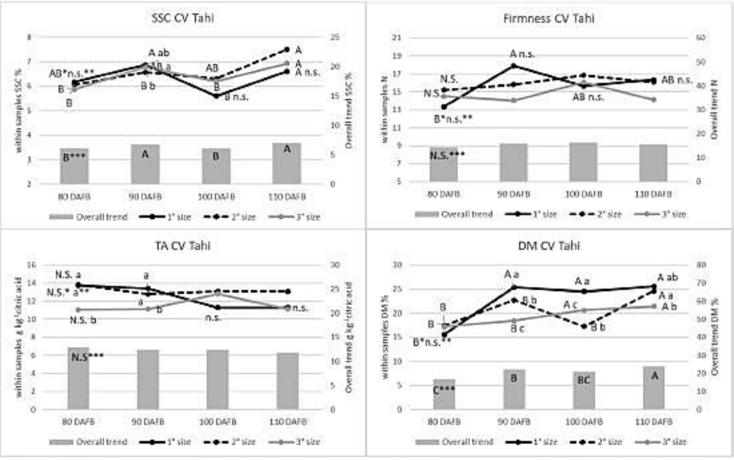


**Fig. 2.** Soluble Solid Content (SSC), firmness, Titratable acidity (TA) and Dry matter (DM) values of the *Actinidia arguta* cultivar Hortgem Tahi over time.
*Different capital letters (A–C) show significant differences (*p*-value ≤ 0.05) within treatment. **Different minor letters (a–c) show significant differences among treatments (*p*-value ≤ 0.05) for each harvesting date. *** Different capital letters (A–C) show significant overall (average of samples grouped for sampling date) differences (*p*-value ≤ 0.05) for each harvesting date.

the most consistent trend throughout sampling dates, with all sample size categories increasing at the end of sampling dates (Figs. 1 and 2). Concerning cv Rua, the average rate of DM increase was around 20 % and similar to that of other kiwifruit species (Bok et al., 2017). The DM content of cv Tahi was higher at all sampling dates, suggesting that this cultivar was already in an advanced stage of maturity when compared with cv Rua.. Firmness and TA of cv Tahi did not present significant differences between 80 DAFB and 110 DAFB, while SSC was enhanced only for 2° and 3° size samples (Fig. 1). Regarding cv Rua (Fig. 2), significant differences were found within each sample throughout sampling dates also for other physicochemical parameters such as SSC, firmness and TA, although for TA, the overall trend was not significantly different. The results from both varieties considering TA were in agreement with the findings of Kim et al. (2012), who observed no changes in the total organic acid concentration during the harvesting period, but rather a change in the acidic composition.

Trends of firmness and SSC values presented a consistent behaviour, with SSC being higher and firmness being lower at the end of the sampling period. Firmness did not differ among sizes in all sampling dates, and the samples displayed a gradual behaviour over time, while the values of SSC and DM were subjected to more drastic changes considering the 1° size category sample over the last two sampling dates. This finding was similar to the observations of Salzano et al. (2018) and was expected in this assessment since rapid softening of fruit might occur in *A. arguta* species during fruit transition to the consumption stage, which was not achieved during this assessment. This trend has been described to occur within a short time frame, along with a low change rate of SSC and DM, rendering the detection of a harvesting index (Hassall et al. (1998)).

For the cultivar Tahi, the SSC among different harvesting dates was stable, while the DM continued to increase; differences between the SSC trends of these two varieties have also been described previously (Hassall et al. (1998)). The possibility of measuring both soluble and insoluble compounds, such as starch, which may enable a better prediction of the SSC of the final product, has led to the use of DM as a maturity indicator for kiwifruit (Crisosto et al., 2012), as DM contains also the precursors of secondary metabolites that undergo considerable changes during fruit ripening and hence determine the quality of ripe fruit (Nordey et al., 2019). However, the different patterns of DM and SSC described in this work and detected in previous works in different selections of *A. arguta* compared to *A. deliciosa*, along with variations that might occur across different seasons, do not encourage the adoption of SSC and DM as maturity indicators for *A. arguta*, as suggested in Hassall et al. (1998).

The trends of the colorimetric parameters were similar for the two cultivars (Fig. 3). At 110 DAFB, all parameter values were decreased for all size samples, with the exception of a* values, which were increased when compared to 80 DAFB. These results indicate that cv Rua, which may develop an inner and an outer red colour, remained with a green skin during quality assessment. It has been suggested that the development of coloration in selections that redden occurs too late, when the fruit is too soft, to be considered as a harvesting index (Hassall et al. (1998)); thus, this trend was expected considering the long-term storage criteria used in this work. Even though both cultivars retained an outer green colour, these results suggest that colorimetric measures could be a valuable way to detect small changes during harvesting. All parameters presented a reduction rate of 3–9%, with the exception of the Hue angle (h*), which only changed by 0.1 %. This was expected, since colour change in green fleshed kiwifruit is mainly described by quantitative colorimetric parameters rather than qualitative ones (Hue). In contrast to the findings of Fisk et al. (2006), where colorimetric analysis did not provide a proper absolute average value of a*, b* and Hue angle, suggesting fruit presented yellow flesh, in this work, Hue angle values ranged from 115 to 125, indicating a green-yellow colour of both cultivars (Voss, 1992).

Reduction of L* and Chroma (C*) values have been described in postharvest quality assessments (Pathare et al., 2013), but few articles have described the same trend for pre-harvesting quality. Our results indicate that in both cultivars, the initial green pale colour evolves into a darker colour, as already mentioned by other authors for different *A. arguta* (Fisk et al., 2008) and *A. deliciosa* cultivars (Taticharoen et al., 2014). Further, it is suggested that samples lose their colour intensity, described by Chroma's trend. There were also significant changes in parameters related to the taint of colour, especially a*.

Regarding the nutraceutical trend, Tables 1 and 2 reveal that TCHL values decreased for almost all sample size categories of both cultivars, while, despite small fluctuations, the trend of other nutraceutical parameters were relatively stable, considering values at 80 and 110 DAFB. This is in agreement with Kim et al. (2012),who found that the vitamin C content remained stable after 50 DAFB. Only the TPC overall trend of the cultivar Rua increased, although this was not the case for all sample sizes. In increase of the TPC content for this cultivar was expected since flesh colour changes to red typically 100 d after anthesis (Mcneilage et al., 2004), similar to another cultivar of *A. arguta* in which the flesh began to turn red around 90 DAFB and reached the maximum intensity by 120 DAFB (Li et al., 2018). Thus, it is suggested that the increase of TPC is mainly due to anthocyanin accumulation.

### 3.2. MFA and PLS models

The MFA model was created to evaluate which parameters are more related with the harvesting quality evolution for each cultivar, in this analysis represented by the supplementary variable "harvesting" that grouped the sampling dates. The MFA scree plots of both cultivars showed that the first two dimensions accounted for most of all meaningful variance, with both dimensions representing around 50 % of the total variance explained (Rua cv 54.78 %, Tahi cv 46.52 %). The scree plot for the cultivar Tahi suggests that dimension 3 should be kept in the model. However, since "Harvesting group" displayed a significant correlation only with dim 1, dimension 3 was not considered in this work.

In the MFA contribution plot (Fig. 4), "colour" and "physicochemical" groups are well correlated with dimension 1, while "nutraceutical" group is more correlated with dimension 2. Supplementary variables ("harvesting" and "size") have no influence on MFA dimensions, but they are used to help with interpretation of the analysis results. In this work, it is suggested that, at a global level, harvesting quality trend is better described by colorimetric and physicochemical parameters, demonstrated by both their proximity on the MFA contribution plot and the higher correlation with dimension 1, especially in the case of cv Tahi.

Regarding the cultivar Rua, the "harvesting" variable shared also an important quote of variance with dimension 2, meaning that some of the nutraceutical parameters might have contributed to the evolution of harvesting quality throughout sampling dates. Thus, visualising the factor map at the single parameter level is needed to obtain a deeper understanding of the relationships among the different variables.

By overlapping the biplot of single parameters with the contribution plot, it is suggested that parameters most correlated with dimension 1, and thus, with the progression of the harvesting period of both cultivars, are almost all the single colorimetric parameters (with the exception of L* and b* for cv Tahi, in which the *p*-value of the correlation coefficient was not significant) and, as expected, the physicochemical parameters SSC and DM. The new colorimetric composite indices (Mic, H_index and a_index) significantly correlated with dimension 1 and harvesting period, with the exception of the a_index for cv Rua. Firmness was well correlated with dimension 1 only for cv Rua, while for cv Tahi, the parameter did not present a significant correlation with any of the MFA dimensions. Considering nutraceutical parameters, the cultivars did not display a common pattern, with cv Rua being better described only by TPC during the harvesting period, while cv Tahi seemed to be described in particular by TCHL and AC. According to early studies, red pigmentation of kiwifruit is due to the accumulation of anthocyanins (Li et al., 2018), which were probably detected by TPC analysis in this work. The use of phenolic content as a ripening indicator is becoming widespread in the literature due to the development of new LED-based devices, such as Multiplex (Agati et al., 2013). Although, to our knowledge, this is mainly applied to wine and table grapes (Bahar et al. (2014)). The trend of TPC in this work suggests that it could be possible to extend the use of those innovative instruments to determine the harvesting time for kiwifruit species.

Based on the MFA results, we can determine which variables are

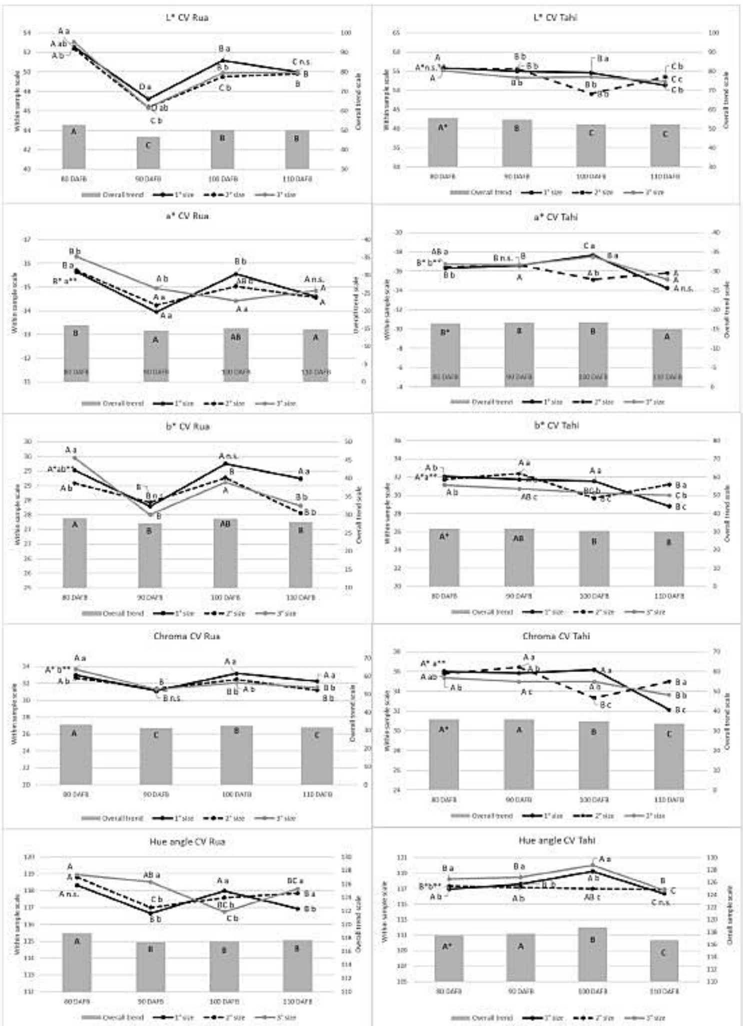


**Fig. 3.** L*, a*, b*, Chroma and Hue angle values of *Actinidia arguta* cultivars Hortgem Rua and Hortgem Tahi over time.
*Different capital letters (A–C) show significant differences ($p$-value ≤ 0.05) within treatment. **Different minor letters (a-c) show significant differences among treatments ($p$-value ≤ 0.05) for each harvesting date. *** Different capital letters (A–C) show significant overall (average of samples grouped for sampling date) differences ($p$-value ≤ 0.05) for each harvesting date.

more correlated with the progression of the harvesting period for each cultivar. However, it is not possible to relate colorimetric and nutraceutical parameters with the harvesting quality trend represented by the physicochemical quality previously validated for long-term storability, mostly because MFA is a non-constrained technique only used in this work for an explanatory purpose. Therefore, it is not possible to identify and quantify how much the parameters are correlated at the level of a single parameter and at the level of a composite

**Table 1**
Total chlorophyll content (TCHL), total polyphenol content (TPC), antioxidant capacity (AC), β-carotene level and vitamin C content (VIT_C) of *Actinidia arguta* cultivar Hortgem Rua.

| Parameters | Size | 80 DAFB | | 90 DAFB | | 100 DAFB | | 110 DAFB | |
|---|---|---|---|---|---|---|---|---|---|
| TCHL (mg L$^{-1}$) | 1° size | 4.7 | N.S.*ab** | 6.4 | n.s. | 6.5 | n.s. | 5.9 | a |
| | 2° size | 6.5 | A a | 5.9 | AB | 5.6 | AB | 4.4 | B b |
| | 3° size | 5.6 | AB b | 7.6 | A | 5.6 | AB | 4.0 | B b |
| | Overall trend | 5.6 | AB*** | 6.6 | A | 5.9 | AB | 4.8 | B |
| TPC (mg kg$^{-1}$ GAE) | 1° size | 1,272.1 | N.S.* n.s.** | 1249.5 | n.s. | 1,340.6 | n.s. | 1,266.0 | n.s. |
| | 2° size | 1,100.5 | B | 1,342.2 | AB | 1,103.5 | B | 1,426.3 | A |
| | 3° size | 1,099.5 | N.S. | 1,242.6 | | 1,060.4 | | 1,296.8 | |
| | Overall trend | 1,157.4 | B*** | 1278.1 | AB | 1,168.1 | B | 1,329.7 | A |
| AC (mol kg$^{-1}$ $Fe^{2+}$) | 1° size | 0.121 | N.S.* n.s.** | 0.121 | n.s. | 0.121 | n.s. | 0.120 | n.s. |
| | 2° size | 0.120 | N.S. | 0.120 | | 0.119 | | 0.122 | |
| | 3° size | 0.120 | N.S. | 0.119 | | 0.117 | | 0.119 | |
| | Overall trend | 0.120 | N.S.*** | 0.120 | | 0.119 | | 0.121 | |
| β-carotene (mg kg$^{-1}$) | 1° size | 1.6 | B*n.s.** | 2.1 | AB n.s. | 2.5 | A n.s. | 2.6 | A a |
| | 2° size | 2.3 | N.S. | 2.1 | | 2.3 | | 1.5 | |
| | 3° size | 1.7 | AB | 2.6 | A | 2.0 | AB | 1.7 | B b |
| | Overall trend | 1.9 | N.S.*** | 2.3 | | 2.3 | | 1.9 | |
| VIT_C (g kg$^{-1}$) | 1° size | 481.7 | N.S.* n.s.** | 539.7 | n.s. | 365.4 | n.s. | 468.2 | b |
| | 2° size | 463.6 | N.S. | 385.8 | | 429.9 | | 607.3 | c |
| | 3° size | 524.8 | B | 383.5 | C | 409.5 | C | 379.6 | A a |
| | Overall trend | 490.0 | N.S.*** | 436.3 | | 401.6 | | 485.0 | |

* Different capital letters (A–C) show significant differences ($P \leq 0.05$) within treatment.
** Different lowercase letters (a–c) show significant differences among treatments ($P \leq 0.05$) for each storage time.
*** Different capital letters (A–B) show significant overall (average of samples grouped for sampling date) differences over time.

parameter (or construct) with the harvesting quality trend. Therefore, a PLS model was created for each cultivar to quantify the relationships among single parameters, composite parameters and harvesting quality evolution. It is worth remembering that the main goal of using different quality techniques for harvesting quality assessment is to enhance the synergy between parameters to obtain better predictions (Borràs et al., 2015). On the other hand, the drawback of this approach is that the increase in information obtained by adding more data may not compensate for the amount of irrelevant variance introduced by the addition of the same (Biancolillo et al., 2014). Therefore, as a consequence of the evaluation of MFA's loading *p*-values, the nutraceutical parameter Vit_C, which was the only parameter not significantly correlated with any of the MFA dimensions for both cultivars, was not introduced in the regression model.

Currently, in the field of modelling, it is not clear how a construct should be classified (Andreev et al., 2009). Some authors stated that the choice should be made first based on theoretical considerations (Roberts and Thatcher (2009)). Despite the different concepts involved in a construct classification, in this work, setting "colour_trend" and "harvesting_index" as reflective constructs was the only possible path since the high correlation among parameters within the same construct would give rise to multicollinearity problems if the same were set formative (Andreev et al., 2009). The presence of severe multicollinearity among parameters might lead to negative loadings, even though this is not reasonably possible theoretically (Hair et al., 2016). On the other hand, nutraceutical parameters could not have been set as reflective, since the loading of the TCHL parameter was not sufficiently high when the reflective measurement type (mode A) was applied. In fact, on the

**Table 2**
Total chlorophyll content (TCHL), total polyphenol content (TPC), antioxidant capacity (AC), β-carotene level and vitamin C content (VIT_C) of *Actinidia arguta* cultivar Hortgem Tahi.

| Parameters | Size | 80 DAFB | | 90 DAFB | | 100 DAFB | | 110 DAFB | |
|---|---|---|---|---|---|---|---|---|---|
| TCHL (mg L$^{-1}$) | 1° size | 7.0 | AB* n.s.** | 9.8 | AB n.s. | 5.5 | B b | 5.2 | B b |
| | 2° size | 10.6 | A | 9.1 | AB | 7.2 | A a | 8.4 | AB a |
| | 3° size | 10.9 | A | 7.9 | AB | 8.2 | AB a | 6.7 | B ab |
| | Overall trend | 9.5 | A*** | 8.9 | AB | 7.0 | B | 6.7 | B |
| TPC (mg kg$^{-1}$ GAE) | 1° size | 1947.8 | A*a** | 1559.7 | B n.s. | 1,730.5 | B n.s. | 1,708.3 | B n.s. |
| | 2° size | 1763.0 | N.S. b | 1,419.3 | | 1,607.3 | | 1,603.3 | |
| | 3° size | 1321.1 | N.S. c | 1,662.9 | | 1,420.8 | | 1,489.3 | |
| | Overall trend | 1677.3 | N.S.*** | 1547.3 | | 1,586.2 | | 1,600.3 | |
| AC (mol kg$^{-1}$ $Fe^{2+}$) | 1° size | 0.109 | N.S.*n.s.** | 0.115 | n.s. | 0.119 | n.s. | 0.115 | n.s. |
| | 2° size | 0.115 | N.S. | 0.103 | | 0.112 | | 0.116 | |
| | 3° size | 0.108 | N.S. | 0.118 | | 0.107 | | 0.119 | |
| | Overall trend | 0.111 | N.S.*** | 0.112 | | 0.113 | | 0.116 | |
| β-carotene (mg kg$^{-1}$) | 1° size | 1.9 | N.S.*n.s.** | 2.8 | n.s. | 1.9 | b | 2.5 | n.s. |
| | 2° size | 2.6 | N.S. | 2.2 | | 2.6 | a | 2.6 | |
| | 3° size | 2.9 | N.S. | 2.3 | | 2.6 | a | 2.1 | |
| | Overall trend | 2.4 | N.S.*** | 2.4 | | 2.3 | | 2.4 | |
| VIT_C (g kg$^{-1}$) | 1° size | 381.2 | A* ab** | 385.4 | A a | 248.1 | B n.s. | 338.7 | A b |
| | 2° size | 389.1 | A a | 331.5 | B b | 269.8 | C | 288.8 | BC b |
| | 3° size | 340.0 | A b | 270.3 | A c | 242.0 | B | 407.0 | A a |
| | Overall trend | 370.1 | A*** | 329.0 | A | 253.3 | B | 344.8 | A |

* Different capital letters (A–C) show significant differences (*p*-value $\leq 0.05$) within treatment.
** Different lowercase letters (a–c) show significant differences among treatments (*p*-value $\leq 0.05$) for each harvesting date.
*** Different capital letters (A–B) show significant overall (average of samples grouped for sampling date) differences (*p*-value $\leq 0.05$) for each harvesting date.

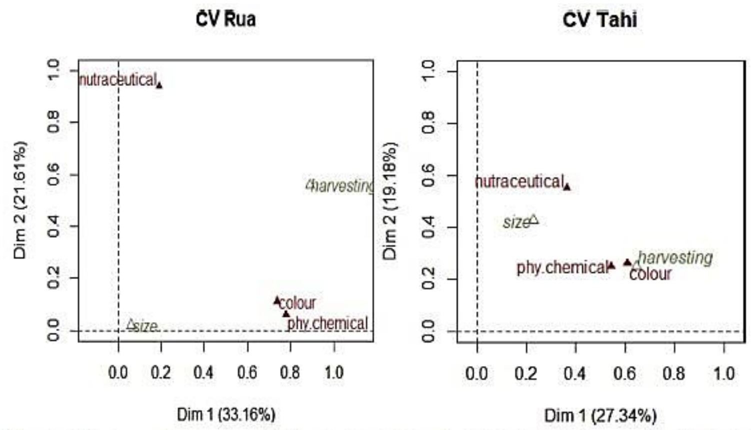


**Fig. 4.** Contribution plot. Biplot of composite parameters on the dimensions 1 and 2 after analysis of physicochemical (represented by "phy.chemical"), colour and nutraceutical attributes of both *Actinidia arguta* cultivars Hortgem Rua and Hortgem Tahi. Active groups ("colour", "phy.chemical", and "nutraceutical" variables) are represented by red colour, while supplementary variables (harvesting and size) are represented by grey colour.

MFA maps, it is possible to observe that nutraceutical parameters were less intra-correlated when compared to colorimetric and physicochemical parameters. This is probably due to the different chemical patterns that characterise the formation and degradation of those compounds during the harvesting period, which in turn make them multidimensional and not interchangeable, as reflective indicators should be (Andreev et al., 2009).

The PLS models allow no assumptions about the population or scale of measurements. However, it requires some assumptions to be fulfilled (Haenlein and Kaplan (2004)). Selective ratios are a valuable way to assess PLS assumptions and to decide which parameters should be included in the model, especially in the case of reflective constructs, where parameters need to be positively correlated (Haenlein and Kaplan (2004)), have a strong mutual association, be well explained by their latent variable and better correlated with their own construct compared to the others (Sanchez, 2013). In the case of cv Rua, Fig. 5 shows that SSC, firmness and DM are positively correlated to each other, although firmness is located at the opposite side of the map, displaying a negative correlation with the other variables. This is due to the fact that firmness decreased during the harvesting period, while the other parameters, SSC and DM, increased. Therefore, the firmness values of cv Rua were multiplied by -1 to improve the unidimensionality of the harvesting trend construct. In the case of cv Tahi, this parameter was removed from the PLS model since it did not present a decreasing linear trend, leading to an insufficient loading value (< 0.70) and to communalities within its construct (< 0.50) (Sanchez, 2013). The TA was eliminated from the models for both cutivars for the same reason, which is not surprising considering that its values were not significantly different comparing the first and the last sampling dates, despite the fluctuations, and the parameter was only well correlated with dimension 2 in the MFA plot.

The same modifications were extended for colorimetric and nutraceutical parameters. The a*, MIC and H_index parameters were multiplied by -1 for both varieties to enforce the unidimensionality of the construct. As a result, based on selective ratio values and correlations with MFA dimensions, the PLS model of cv Rua was composed of L*, a* (multiplied by -1), b*, Chroma, Hue angle, Mic (multiplied by -1), H_index (multiplied by -1), TCHL, TPC, beta-carotene, SSC, DM, sampling dates and firmness (multiplied by -1), while that of cv Tahi included a* (multiplied by -1), Chroma, Hue angle, Mic (multiplied by -1), H_index (multiplied by -1), a_index (multiplied by -1), TCHL, AC, beta-carotene, SSC, DM, sampling dates. All operations were fundamental in order to obtain acceptable values of Cronbach's alpha (C.alpha) and Dillon-Goldstein's rho (DG Rho), indices of reflective constructs asdemonstrated in Table 3 (Sanchez, 2013).

Figs. 6 and 7 confirm the results obtained in the MFA: TPC was the parameter among nutraceutical indicators with the highest loading value in case of cv Rua, while for cv Tahi, the parameter with the highest loading value was TCHL. As seen in Figs. 6 and 7, although beta-carotene shows a low loading value, the parameter was kept in both cultivar models since it is advisable to keep at least three parameters for each construct (Boccuzzo and Fordellone (2015)).

Among the colorimetric parameters, H_index and Mic displayed the highest loadings, along with the a* parameter for both cultivars. These results suggest that a common colorimetric harvesting index for both cultivars could fit better than a nutraceutical one in a combined model, with the condition that colour assessment considers only the outer part of the fruit. Surprisingly, the H_index had one of the highest values considering the small variations of the parameter Hue angle in the univariate assessment, which led to smaller loading values of the Hue angle in the MFA, being only higher than a_index and b* in the models for both cultivars. This study suggests that colour change sensitivity can be enhanced by the use of quantitative colorimetric parameters, such as L* and chroma, combined with Hue assessment.

Considering the structural part of the analysis, that is, the impact of the "nutraceutical_trend" and the "colorimetric_trend" constructs as global indicators, only the model for cv Rua presented a significant impact of both predictors on the dependent variable harvesting_index ($p$-values < 0 .05 and < 0.001 for "colour_trend" and "nutraceutical_trend", respectively). We found an $R^2$ of 0.83 and a goodness of fitness of 0.74 for cv Rua, while for cv Tahi, the model presented an $R^2$ of 0.44, which is considered a moderate value (Boccuzzo and Fordellone (2015); Sanchez, 2013), and a goodness of fitness of 0.53. The lower quality of the Tahi model might be due to an inconsistent trend of physicochemical parameters throughout the harvesting period, as suggested by ANOVA results, and to the fact that the model was built based

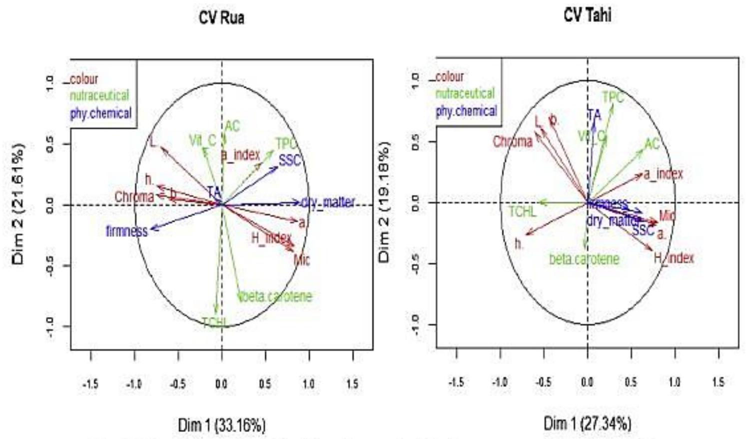


Fig. 5. Biplot of colour, physicochemical and nutraceutical single parameters on dimensions 1 and 2.

**Table 3**
Cronbach's (C.alpha) alpha and Dillon-Goldstein's rho (DG Rho) values of the latent constructs of the *Actinidia arguta* cultivars Hortgem Tahi and Hortgem Rua.

| Cultivars | Latent constructs | C.alpha | DGRho |
|---|---|---|---|
| Rua cv | colour_trend | 0.96 | 0.97 |
| | nutraceutical_trend | 0.00 | 0.00 |
| | harvesting_index | 0.93 | 0.95 |
| Tahi cv | colour_trend | 0.95 | 0.96 |
| | nutraceutical_trend | 0.00 | 0.00 |
| | harvesting_index | 0.81 | 0.89 |

on two dimensions provided by MFA, accounting for less than 50 % of its explained variance. Thus, parameter selection was based on a poor explanatory model. We assume that the samples of cv Tahi were already in an advanced maturity stage, which in turn did not enable the detection of linear trends of parameters throughout sampling dates.

In this research, the path coefficient of the "nutraceutical_trend" construct was higher than that of the "colorimetric_trend" one (0.76 and 0.36, respectively). This result was not expected, since MFA demonstrates an overall better correlation of colorimetric parameters with harvesting period than the nutraceutical ones. This may be explained by the choice of setting "nutraceutical_trend" as a formative rather than a reflective construct. The use of formative constructs leads to higher values of path coefficients, since the mode B (formative measurement type) calculation takes into account both the correlation among predictors and the latent variable and the intercorrelation among predictors (Sanchez, 2013), which might have enhanced the model's shared variance. It is accepted that the regression weight calculation can outperform the correlation, and mode B is more susceptible to overfitting rates than mode A (Becker et al., 2013). Model B also seems to enhance $R^2$ values, since it capitalises most of the characteristics of the dataset, especially if the sample size is low, as in the present study

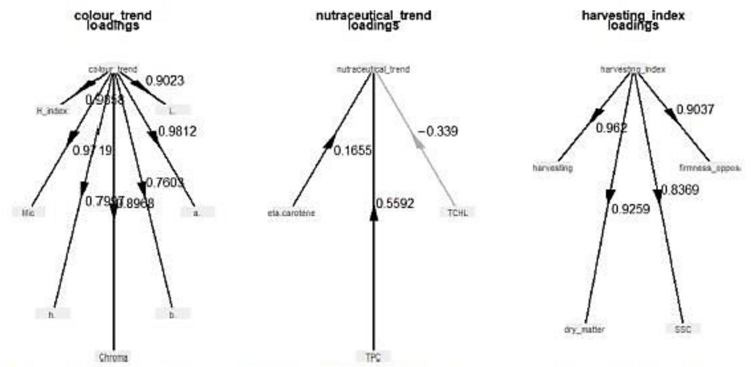


Fig. 6. Loadings between colour trend, nutraceutical trend and harvesting index and their relative parameters of PLS models of the *Actinidia arguta* cultivar Rua.

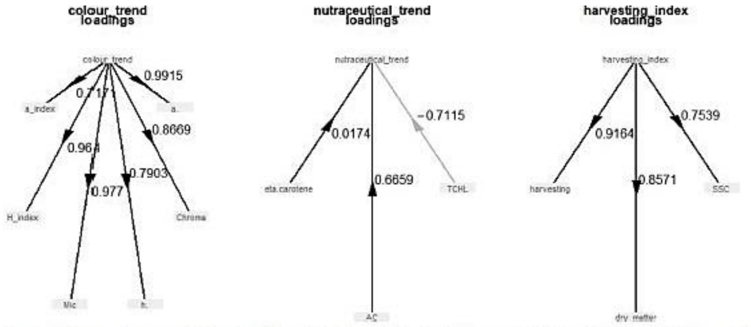


Fig. 7. Loadings between colour_trend, nutraceutical_trend and harvesting_index and their relative parameters of PLS models of the Actinidia arguta cultivar Hortgem Tahi.

(Becker et al., 2013). In fact, even though the path coefficient of the "colormetric_trend" construct was lower, it significantly impacted bootstrapping validation, while the same was not true for the "nutraceutical_trend" construct. Considering the small size of both cultivar samples in this work, it is advisable to use higher samples sizes in order to extend the results to the population and to replicate the experiment across different years.

## 4. Conclusions

Our study provides useful information about trends of different harvesting parameters of *A. arguta* cultivars and presents a novel methodology for harvesting index investigation by using two different multivariate approaches to select and build a harvesting index model. We suggest that more attention should be given to colorimetric indices and their combination, which appear to be more sensitive to changes and less cultivar-specific than nutraceutical parameters during harvesting, as suggested by MFA results and, partially, by PLS modelling. However, our work has several limitations, such as the amount of data, which needs to be extended to larger samples, being obtained from different harvesting years and, possibly, different territories. We also would like to point out that the proposed methodology only takes into account linear relationships among parameters. Therefore, parameters that might display a non-linear trend throughout the harvesting period need to be assessed using different types of statistical models.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## CRediT authorship contribution statement

**Thais Mendes da Silva:** Formal analysis, Methodology, Visualization, Software, Writing - original draft. **Rossella Briano:** Methodology, Investigation. **Cristiana Peano:** Methodology, Conceptualization, Supervision. **Nicole Roberta Giuggioli:** Validation, 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.


## Acknowledgements

We would like to thank the private company Ortofruititalia soc.-coop. S.R.L., Saluzzo (CN), Italy, for supplying the samples using in this research.


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# Conclusions

In this Ph.D. program, the goal of developing quality assessments under different marketing strategies to obtain a better understanding of relationships among parameters and sensory attributes over different crops has been achieved sufficiently. In this research, each of the three steps concerning the development of new analytical, sensory and statistical protocols was subjected to specific actions of improvements, which have included the proposition of several strategies to solve the drawbacks of conventional methods.

Concerning the first step of this research, the improvements made on the creation and management of the analytical data regarded mainly the creation of composite indexes through the combination of single parameters derived from new and conventional instrumentation. The composite indexes were important to better represent complex or global quality attributes such as colour and texture, allowing the researcher to integrate the measurements in a way that is more related with a sensory attribute. In all articles, the combination was performed by either creating manually new calculations with the instrumentation's original parameters (e.g. colorimetric indexes) or fusing parameters under constructs with statistical techniques such as the MFA or the PLS models, with the latter having the advantage of not determining *a priori* the weight of parameters or the relationship among them in the construct. In fact, considering our results, not all indexes derived from calculation have turned to be better indicators than the conventional parameters.

The introduction of calculations and constructs based on analytical data has provided information concerning the relation among parameters and the sensory attributes and their suitability for specific crops. In particular, our work provides detailed information on how and why the use of simplistic indicators can mislead or are not sufficient to estimate sensory attributes. Some examples are the use of TSS, the ratio TSS/TA or BrimA (TSS – acidity* *k*) to measure sweetness in different crops (Mendes da Silva et al., 2019a; Mendes da Silva et al., 2019b) or the use of firmness measured with the penetrometer to indicate the sensory attribute hardness (Mendes da Silva et al., 2021). Our work also illustrates that the choice and interpretation of parameters derived from new instrumentation such as colorimeter and texture analyzer are crop dependent and we provide important information considering which parameters should be used and how they should be interpreted for specific crops (Mendes da Silva et al., 2021; Giuggioli et al. 2020).

However, despite the results achieved, we do recognize that in this project the quality assessments were not always performed over several years and some of them are actually only concentrated in 1 year, which means that our considerations still need to be validated in further research trials. Furthermore, it was not possible to include other relevant instrumentation in the project in order to provide detailed information that concerns aroma of products, such as the electronic nose. This loss of information was accepted by the research program considering that, with the exception of off-notes, consumers are often not able to distinguish specific aroma notes of a product and the overall liking is often linked to a general and acceptable note of aroma related to a determined product and its intensity rather than its qualitative profile.

Concerning the second step of this project, it can be concluded that the new sensory methods employed on product's characterization (projective mapping and CATA) were efficient as assessors, being them semi trained people or consumers, were able to distinguish different versions of products that were subjected to the assessments. In fact, in all assessments, their judgments were in agreement with previous literature of trained panels regardless if assessors were subjected to full training, theoretical training (Mendes da Silva et al. (2019b) or no training at all. Moreover, the obtained data was validated with the innovative statistical approaches: the combinatory calculus for what concerns the projective mapping and the NM-PLS model following the Penalty analysis of CATA results. Thanks to the statistical approach, the number of attributes to be considered relevant for a specific product version or for the overall liking judgement is not determined *a priori,* reducing the arbitrariness of interpretation. However, it is important to note that a huge drawback of our work was the impossibility to validate data with different groups of assessors or to recruit a large number of consumers. We hope the developed methodologies will be applied by other researches in order to confirm their efficacy.

Finally, considering the third part of this research, the use of complex multivariate statistical models such as PLS, NM-PLS, MFA were vital in order to deal with many critical aspects of quality assessments. To begin with, the possibility of using models that manage data of different type (continuous, ordinal or categorical) allowed the researcher to perform an integrated evaluation, without losing important information concerning the interaction among analytical parameters and sensory attributes. Moreover, with those models, it was possible to aggregate single parameters obtained by analytical instrumentation, such as colorimeter and texture parameters, to obtain constructs that represent a global attribute. At the level of a single construct, this was very important considering that parameters derived from colorimeter and texture analyzer are complementary to represent colour and texture of products. Moreover, when applying the multivariate model with this approach, the data is better represented in the multivariate global space (model's dimensions) as the iterative process that enables the creation of model's dimensions is mostly governed by the global constructs that are weighted and balanced among each other rather than a single set of very heterogenous parameters coming from different analytical or sensory sources. This prevents that a single parameter that is naturally characterized by a higher variability will have a major influence on model's dimension. Moreover, in this way, it is possible to assess samples is a space that reproduces consumer behavior, which may not focus their attention on a set of specific attributes, instead, they integrate all the descriptors of the product to reach a global consensus.

Finally, we also demonstrated that in some cases, it is important to use constrained techniques in order to relate parameters or sensory attributes to the liking judgment of products. In our work, this strategy has been adopted especially when the parameters that are the main cause of differences among samples are not the ones related with the liking of products. By using constrained techniques such as the PLS model (or its variation to the nonlinear case NM-PLS), it is possible to split the database in dependent and independent constructs, which in turn allows the creation of dimensions by maximizing the variation of the dependent variables and this is vital to obtain a common space where the dependent variable of interest, such as liking (Mendes da Silva et al., 2021) or the harvesting quality (Mendes da Silva et al., 2020a) is well explained (well represented in the common space). Moreover, the PLS and the fuzzy model allows the user to set different type of relationships between the dependent and the independent data, which is very important in quality assessments as many quality attributes, especially those concerning the texture of products, display a nonlinear relationship with liking. And finally, those models are also suitable for quality assessments with small data, which was the main drawback of our works.

We also highlighted the importance of using models that deal with the uncertainty linked to the human judgement such as the uncertainty present in sensory assessments. All quality assessments involving sensory tests performed throughout time (such as those under the branding strategy) have foreseen the use of ANOVA mixed models where the random variance derived from assessor's judgment can be accounted (Mendes da Silva et al., 2019a) or modelled (Mendes da Silva et al., 2021) and this is very important to reduce the model's error term and reduce the possibility of committing the type error 1 rate of fixed effects, meaning that the null hypothesis (i.e. no significant differences among samples) might be rejected when it should be accepted. Moreover, this type of model is able to handle missing data linked to the fact that assessors may not be able to participate to all sensory sessions throughout time within a same quality assessment. This characteristic is vital for companies such as Sata SRL'S, where the employee's routine do not allow a single assessor to be always present in the company to perform all sensory sessions. This also meets a more general need of panel leaders from different companies who might face repeatably the "turn over" process of company's personal, which may happen during the course of a quality assessment. Finally, also in the multivariate case we present the fuzzy model as a solution to deal with human uncertainty. Even though the current literature describes the need of expert knowledge as a drawback of the model, for consulting firms such as Sata SRL, it represents a potential instrument to develop tailored tools for clients based on the company's knowledge.

Overall, the use of R software was vital to develop the quality assessments under the statistical point of view as this tool allows the user to choose freely the type of model that is most appropriate to solve the quality assessment’s critical aspects. We hope that the R codes shared in the annex of this document may hope researches to perform quality assessments with a better performance and reduce the time a food technologist devotes to gather data and analyze it. Therefore, a food technologist can dedicate more time to the final part of a quality assessment, which is to interpret, display and share the results to other researchers, clients or other interlocutors, increasing the impact of his work.

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# Annex 1- Some of the R codes used in this research:

1. The fuzzy model created in the article: A novel statistical approach to assess the quality and commercial viability of a retail branded perishable fruit:

```
#install the “sets” package

install.packages("sets")

#recall the “sets” package

require(sets)

#define the range of sensory attributes values

sets_options("universe", seq(1, 9, 0.5))#the sensory attributes function will vary from 1 to 9

#set the fuzzy functions for each sensory attribute (fuzzification step of numerical variables) and store it the object “variables”

variables <- set(hardness = fuzzy_partition(varnames = c(low = 1, good = 5, high = 9),sd = 1.19), aroma = fuzzy_partition(varnames = c(scarce = 1, good = 5, excellent = 9),sd = 1.48), juiciness= fuzzy_partition(varnames = c(low = 1, intermediate = 5, high = 9), sd = 1.19), overall_liking = fuzzy_partition(varnames = c(scarce = 1, ok = 5, excellent = 9), FUN = fuzzy_cone, radius = 1.1))

#set the rules of model and store it in the object “rules”

rules <- set(fuzzy_rule(aroma %is% scarce && juiciness %is% low && hardness %is% good, overall_liking %is% scarce),

            fuzzy_rule(aroma %is% good && juiciness %is% low && hardness %is% good, overall_liking %is% ok),

            fuzzy_rule(aroma %is% excellent && juiciness %is% low && hardness %is% good, overall_liking %is% ok),

            fuzzy_rule(aroma %is% scarce && juiciness %is% intermediate && hardness %is% good, overall_liking %is% ok),

            fuzzy_rule(aroma %is% scarce && juiciness %is% high && hardness %is% good, overall_liking %is% ok),

            fuzzy_rule(aroma %is% excellent && juiciness %is% high && hardness %is% good, overall_liking %is% excellent),

            fuzzy_rule(aroma %is% excellent && juiciness %is% intermediate && hardness %is% good, overall_liking %is% excellent),

            fuzzy_rule(aroma %is% good && juiciness %is% high && hardness %is% good, overall_liking %is% excellent),
```

*fuzzy_rule(aroma %is% good && juiciness %is% intermediate && hardness %is% high , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% intermediate && hardness %is% high , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% excellent && juiciness %is% intermediate && hardness %is% high , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% good && juiciness %is% low && hardness %is% high , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% low && hardness %is% high , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% excellent && juiciness %is% high && hardness %is% high , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% good && juiciness %is% high && hardness %is% high , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% high && hardness %is% high , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% good && juiciness %is% intermediate && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% low && hardness %is% low , overall_liking %is% scarce),*

*fuzzy_rule(aroma %is% good && juiciness %is% low && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% excellent && juiciness %is% low && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% excellent && juiciness %is% intermediate && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% good && juiciness %is% intermediate && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% intermediate && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% intermediate && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% scarce && juiciness %is% high && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% good && juiciness %is% high && hardness %is% low , overall_liking %is% ok),*

*fuzzy_rule(aroma %is% excellent && juiciness %is% high && hardness %is% low , overall_liking %is% ok))*

*#create the model recalling the objects “variables” and “rules”*

*model <- fuzzy_system(variables, rules)*

*#print and plot the model's function*

*print(model)*

*plot(model)*

*#Defuzzyfication of model: use of real sensory values of independent attributes aroma, juiciness and hardness to obtain values for the dependent attribute overall_linking*

*example.2 <- fuzzy_inference(model, list(aroma = 4,25, juiciness = 3,05, hardness = 7,15))*

*plot(example.2)*

*gset_defuzzify(example.2, "centroid")*

*example.3 <- fuzzy_inference(model, list(aroma = 3,15, juiciness = 3,8, hardness = 6,50))*

*gset_defuzzify(example.3, "centroid")*

*example.4 <- fuzzy_inference(model, list(aroma = 4,0, juiciness = 5,25, hardness = 4,70))*

*gset_defuzzify(example.4, "centroid")*

*example.6 <- fuzzy_inference(model, list(aroma = 4,05, juiciness = 5,25, hardness = 5,20))*

*gset_defuzzify(example.6, "centroid")*

*example.7 <- fuzzy_inference(model, list(aroma = 2,71, juiciness = 2,71, hardness = 4,71))*

*gset_defuzzify(example.7, "centroid")*

*plot(example.7)*

*example.8 <- fuzzy_inference(model, list(aroma = 2,6, juiciness = 2,7, hardness = 3,35))*

*gset_defuzzify(example.8, "centroid")*

*example.9 <- fuzzy_inference(model, list(aroma = 4,15, juiciness = 3,9, hardness = 7,30))*

*gset_defuzzify(example.9, "centroid")*

*example.9 <- fuzzy_inference(model, list(aroma = 4,15, juiciness = 3,9, hardness = 7,30))*

*gset_defuzzify(example.9, "centroid")*

*example.12 <- fuzzy_inference(model, list(aroma = 3,65, juiciness = 4,1, hardness = 7,20))*

*gset_defuzzify(example.12, "centroid")*

*example.13 <- fuzzy_inference(model, list(aroma = 4,5, juiciness = 5,06, hardness = 6,68))*

*gset_defuzzify(example.13, "centroid")* *plot(example.13)*

*example.14 <- fuzzy_inference(model, list(aroma = 4,0, juiciness = 3,19, hardness = 3,87))*

*gset_defuzzify(example.14, "centroid")*

*example.15 <- fuzzy_inference(model, list(aroma = 3,5, juiciness = 3,0, hardness = 5,40))*

*gset_defuzzify(example.15, "centroid")*

2. The data mining process applied in the article: A New Sensory Approach Combined with a Text-Mining Tool to Create a Sensory Lexicon and Profile of Monovarietal Apple Juices:

*#install packages needed to perform the data mining process*

*Needed <- c("tm", "SnowballCC", "RColorBrewer", "ggplot2", "wordcloud", "biclust", "cluster", "igraph", "fpc")*

*install.packages(Needed, dependencies = TRUE)*

*install.packages("Rcampdf", repos = "http://datacube.wu.ac.at/", type = "source")*

*#store the folder path where articles to be subjected to the data mining process are saved in folder C in the object "cname"*

*cname <- file.path("C:", "texts")*

*cname*

*dir(cname)*

*#recall package "tm"*

*require(tm)*

*#create the corpus (the group of articles to be subjected to the data mining process) and store it in the object "docs"*

*corpus<-DirSource(cname)*

*docs <- VCorpus(corpus)*

```
#check the “corpus” general information

summary(docs)

#start the data mining process: Preprocessing of corpus

#remove meaningless words (stopwords) to the process (“and”, “with”, etc)

docs <- tm_map(docs, removeWords, stopwords("english"))

docs <- tm_map(docs, PlainTextDocument)

#remove punctuation (dots, etc)

docs <- tm_map(docs,content_transformer(removePunctuation))

#remove symbols

for (j in seq(docs)) {

  docs[[j]] <- gsub("/", " ", docs[[j]])

  docs[[j]] <- gsub("@", " ", docs[[j]])

  docs[[j]] <- gsub("\\|", " ", docs[[j]])

  docs[[j]] <- gsub("\u2028", " ", docs[[j]])}

# remove anything other than English letters or space

removeNumPunct <- function(x) gsub("[^[:alpha:][:space:]]*", "", x)

docs <- tm_map(docs, content_transformer(removeNumPunct))

#remove numbers

writeLines(as.character(docs[1]))

docs <- tm_map(docs,removeNumbers)

docs <- tm_map(docs, PlainTextDocument)

#transform every word in lowercase

docs <- tm_map(docs, content_transformer(tolower))
```

```
docs <- tm_map(docs, PlainTextDocument)

DocsCopy <- docs

#merge word to create meaningful expression

writeLines(as.character(docs[1]))

for (j in seq(docs))

{docs[[j]] <- gsub("apple aroma", "apple_aroma", docs[[j]])

  docs[[j]] <- gsub("apple taste", "apple_taste", docs[[j]])

  docs[[j]] <- gsub("fruity flavors", "fruity_flavors", docs[[j]])}

docs <- tm_map(docs, PlainTextDocument)

#remove words that are not useful or relevant to the scope

docs <- tm_map(docs, removeWords, c("sensory", "consumers", "juice", "food",
"juices", "analysis", "fruit", "particular", "a", "b", "c", "d", "e", "ca", "et", "al",
"aftertaste", "ns", "ab", "bc", "de", "-", ",", "p", "gl", "ml", "_", """, "g", "t", "l", "mm",
"cb", "l", "eg", "'s", "f", "ac", "ie", " ", "citrus", "±", "sweetapple", "appleapple",
"±"))

#remove the white spaces left from the past remove functions

docs <- tm_map(docs, stripWhitespace)

#transform the corpus in a text document

docs <- tm_map(docs, PlainTextDocument)

##end of preprocessing: Creation of a document term matrix: a document
where rows are articles and words are columns

dtm <- DocumentTermMatrix(docs)

##inspect the matrix in order to assess the degree of sparsity (the number of
rows that are empty. If sparsity is high, a high number of terms are cited few
times
```

```
inspect(dtm)

##convert the text document in a matrix where count of terms is made globally
(not by each article)

freq <- colSums(as.matrix(dtm))

length(freq)

#reorder terms by citation order

ord <- order(freq)

#check more frequent terms

freq[head(ord)]

##inspect least frequently occurring terms

freq[tail(ord)]

##esport the matrix in a excel file

m <- as.matrix(dtm)

dim(m)

write.csv(m, file="DocumentTermMatrix.csv")

###Filtering of terms: remove terms that are less frequent

dtms <- removeSparseTerms(dtm, 0.9) # This makes a matrix that is 90%
empty space, maximum.

dtms

###recheck terms

freq <- colSums(as.matrix(dtm))

freq

###or check terms that are cited at least 3 times

freq2<-findFreqTerms(dtms, lowfreq=2) #termini che compaiono almeno 3 volte
```

```
freq2

#create dataframe and plot it

wf2 <- data.frame(word=names(freq), freq=freq)

View(wf2)

plot(wf2, cex= 0.5)


### measure the frequency of which two terms co-occur (or show up together)
in documents across

#Note also, that it is not an indicator of nearness or contiguity.

findAssocs(dtms, "cooked", 0.5)#the degree of correlation is set to be 0.5

findAssocs(dtms, "candy", 0.5

####build a clustering based on terms association

####reverse the matrix DTM to a TDM

tdm <- TermDocumentMatrix(docs, control=list(wordLengths=c(1,Inf)))

####remove sparsity

tdm2 <- removeSparseTerms(tdm, sparse=0.90)

####transform the text document into a matrix

m2 <- as.matrix(tdm2)

distMatrix <- dist(scale(m2))

####apply the cluster method

fit <- hclust(distMatrix, method="ward.D")

plot(fit)

##### or create a word-net
```

```
tdm <- TermDocumentMatrix(docs, control=list(wordLengths=c(1,Inf)))

tdm2 <- removeSparseTerms(tdm, sparse=0.90)

termDocMatrix <- as.matrix(tdm2)

##### change it to a Boolean matrix

termDocMatrix[termDocMatrix>=1] <- 1

##### transform into a term-term adjacency matrix

termMatrix <- termDocMatrix %*% t(termDocMatrix)

##### inspect terms numbered 5 to 10

termMatrix[5:10,5:10]

install.packages("igraph")

library(igraph)

##### build a graph from the above matrix

g <- graph.adjacency(termMatrix, weighted=T, mode="undirected")

g <- simplify(g)

##### set labels and degrees of vertices

V(g)$label <- V(g)$name

V(g)$degree <- degree(g)

layout1 <- layout.fruchterman.reingold(g)

#####plot thw word-net

plot(g, layout=layout1)

###### create the histogram and the wordcloud

######after cleaning of the DTM matrix with excel, reload the dataset
```

```
Dataset<-read.table("clipboard", header=TRUE, sep="", row.names = 1,
na.strings="NA", dec=",", strip.white=TRUE, stringsAsFactors=TRUE)

###### histogram

install.packages("ggplot2")

require(ggplot2)

p <- ggplot(subset(Dataset, freq>2), aes(x = reorder(word, -freq), y = freq)) +
geom_bar(stat = "identity") +  xlab("Terms") + ylab("Frequencies")+
theme(axis.text.x=element_text(angle=45, hjust=1))

p

#####wordcloud

install.packages("wordcloud")

install.packages("RColorBrewer")

require(RColorBrewer)

library(wordcloud)

wordcloud(Dataset$word, Dataset$freq, colors=brewer.pal(6, "Dark2"),
random.color=F, random.order=FALSE, rot.per=0.3)
```

3. The multiple factor analysis applied on projective mapping data from the article: Evaluation of the quality of ready to eat avocado Cv. Hass, article under review in the journal: International Journal of Food Science and in the article: A New Sensory Approach Combined with a Text-Mining Tool to Create a Sensory Lexicon and Profile of Monovarietal Apple Juices:

```
#install and recall packages

install.packages("FactoMineR")

require(FactoMineR)

#load data

Dataset<-read.table("clipboard", header=TRUE, sep="", row.names = 1,
na.strings="NA", dec=",", strip.white=TRUE, stringsAsFactors=TRUE)

#1° approach: create the MFA model for the projective mapping data as
continuous (either assessor's coordinates and scores) and print biplot of
groups, attributes and samples

res = MFA(Dataset, group=c(2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1,
1,1,1,1,1,1,1),# use assessor's coordinates by grouping them 2 by 2 and use
individually sensory attributes

type=c(rep("c", 22)),# set all data to be continuous, not scaled

ncp=5,#keep 5 dimensions in the model

 name.group=c("Ass1","Ass2", "Ass3", "Ass4", "Ass5", "Ass6", "Ass7", "Ass8",
"Ass9", "Ass10", "Ass11", "Ass12", "firmness", "creaminess", "sweetness",
"bitterness", "flavor intensity", "aroma intensity", "hazelnut notes", "rancid
notes", "grass notes", "overall liking"),#name assessor's coordinates and
sensory attributes

 num.group.sup= c(13, 14, 15, 16, 17, 18, 19, 20, 21, 22),#set sensory
attributes (represented by columns 13th up to 22nd from the uploaded dataset)
as supplementary

 graph=TRUE)#print graphics
```

*##2°approach: create the MFA model for the projective mapping data as continuous (assessor's coordinates) and frequency (assessor's citations) and print biplot of groups, attributes and samples*

*res = MFA(Dataset, group=c(2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 4, 6, 7, 15),#group coordinates of assessors 2 by 2 and group the sensory attributes by type of global attribute*

*type=c(rep("c", 15),"f", "f", "f", "f"), #set assessor's coordinates to be continuous data and group of attributes to be frequency data*

*ncp=5, name.group=c("Ass1","Ass2", "Ass3", "Ass4", "Ass5", "Ass6", "Ass7", "Ass8", "Ass9", "Ass10", "Ass11", "Ass12", "Ass13", "Ass14", "Ass15", "texture", "taste", "aspect", "notes"),#name assessor's coordinates and global attributes*

*num.group.sup= c(16,17,18,19), #set global attributes to be supplementary data*

*graph=TRUE)#print graphics*

4. The NM-PLS model applied on the Penalty analysis results, from the article under review in the Journal of sensory studies: Application of CATA and Non-Metric Partial Least Squares regression to evaluate attribute's perception and consumer liking of apples

```
#install and recall the "plspm" package

install.packages("plspm")

require(plspm)

#create the inner model (global constructs), a matrix where correlations
among independent global constructs and dependent construct are set with
the logical interger 1

texture=c(0,0,0,0)

taste=c(0,0,0,0)

notes=c(0,0,0,0)

liking=c(1,1,1,0)

matrice_inner=rbind(texture, taste, notes,liking)

colnames(matrice_inner)=rownames(matrice_inner)

#plot the inner model

innerplot(matrice_inner)

#load data

Dataset<-read.table("clipboard", header=TRUE, sep="", row.names = 1,
na.strings="NA", dec=",", strip.white=TRUE, stringsAsFactors=TRUE)

#group single sensory attributes by global constructs (outer model) and
store it under the object "blocks"

blocks = list(1:2, 3:4, 5:9, 10)

#set the nature of each variable and store it under the object "scaling":

scaling <- list(c("ORD", "ORD"),
                c("ORD", "ORD"),
                c("ORD", "ORD", "ORD", "ORD", "ORD"),
                c("NUM"))# data from codified Penalty analysis as ordinal,
scores of liking as continuous
```

```
#set global constructs to be reflective (A) or formative (B) and store it under
the object "modes"

modes = c("A", "A", "B", "A")

#create the NM-PLS model and store it as "pls"

pls = plspm(Dataset, matrice_inner, blocks, modes = modes, scaled=T,
scheme= "centroid", scaling =scaling, plscomp = c(1,1,1,1), boot.val = T)

#check unidimensionality of constructs:

pls$unidim

#check the relationships among global constructs (inner model) and among
the single attributes and their own construct (outer model)

plot(pls, what = "inner", arr.width = 0.1, cex= 1.5, cex.txt = 1.5,
colpos="black", colneg="gray")

plot(pls, what = "loadings", arr.width = 0.1, cex= 1.5, cex.txt = 1.5,
colpos="black", colneg="gray")

#check if loadings between single attributes and their own construct

pls$outer_model

#check if loadings between single attributes and other constructs

pls$crossloadings

#check R2 of model:

pls$inner_summary[, "R2", drop = FALSE]

#check model's goodness-of-fit

pls$gof

#perform boostrapp's validation

pls$boot
```

5. The ANOVA mixed model performed on sensory data from article, as described in Mendes da Silva et al. (2021): Modelling strawberry quality in a longitudinal study under the marketing concept of branding

```
#install and recall package "nlme" and "lsmeans"

install.packages("nlme")

require(nlme)

install.packages("lsmeans")

require(lsmeans)

#load data in longformat taking into account the missing data

Dataset<-read.table("clipboard", header=TRUE, sep="", na.strings="",
dec=",", strip.white=TRUE, stringsAsFactors=TRUE)

#create the default anova's model (using the covariance structure
compound symmetry, where correlation patterns among random factor
errors is costant) and store it in the object "lme.Model.1"

lme.Model.1<-lme(Aroma  ~ Samples, #set dependent variable as aroma
and samples as independent fixed factor

 random = list(Assessors = ~ 1) , #set assessors to be a random factor

 data=Dataset, na.action=na.omit) #tell the model there are missing values

#try to improve the model with the AR1 covariance structure, where
correlation patterns among random factor errors declines over time, and
store the model in the object "lme.Model.2"

lme.Model.2<-lme(Aroma ~ Samples, random = list(Assessors = ~ 1),

data=Dataset, correlation = corAR1(),#set the covariance structure to be
autoregressive "AR1"

 na.action=na.omit)

#compare models performance

anova(lme.Model.2, lme.Model.1)
```