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Food Quality 4.0: From traditional approaches to digitalized automated analysis

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ABSTRACT

Food quality has recently received considerable attention from governments, researchers, and consumers due to the increasing demand for healthier and more nutritious food products. Traditionally, food quality is determined using a range of destructive and time-consuming approaches with modest analytical performance, underscoring the urgent need to develop novel analytical techniques. The Fourth Industrial Revolution (called Industry 4.0) is progressing exponentially, driven by the advent of a range of digital technologies and other innovative technological advances. “Food Quality 4.0” is a new concept referring to the use of Industry 4.0 technologies in food analysis to achieve rapid, reliable, and objective assessment of food quality. In this review, we will first discuss the fundamentals and principles of Food Industry 4.0 technologies and their connections with the Food Quality 4.0 concept. Then, the most common techniques used to determine food quality will briefly be reviewed before highlighting the advancements made in analytical techniques to assess food quality in the era of Industry 4.0.

Food Quality 4.0 is characterized by growing digitalization and automation of food analysis using the most advanced technologies in the food industry. Key aspects of Food Quality 4.0, including, among others, non-destructive fingerprinting techniques, omics technologies and bioinformatics tools, Artificial Intelligence and Big Data, have great potential to revolutionize food quality. Although most of these technologies are still under development, it is anticipated that future research will overcome current limitations for large-scale applications.

Keywords: Artificial Intelligence, automation, Big Data, digitalization, food, Industry 4.0, omics, quality, smart sensors, spectroscopy

1. Introduction

The modern food industry is a very competitive and dynamically developing environment, with increasing consumers' demands towards better food quality, safety, and shelf life, more product diversity and adoption of green/eco-friendly/sustainable production. Nevertheless, traditional processing technologies may affect sensory quality characteristics such as appearance, color, taste, and texture due to structural and conformational changes (e.g., lipid oxidation and protein denaturation) in food products. Therefore, to meet the constantly growing consumer demands for food products of high quality, food researchers and the food industry should constantly seek more advanced solutions and technologies, including innovative processing and analytical techniques (Echegary et al., 2022; García-Oliveira et al., 2020; Putnik et al., 2019).

Food quality refers to a range of attributes that are mainly related to sensory traits, shelf life, and freshness of food, but other properties associated with microbiological and technological parameters are also of utmost importance. During food processing and storage by using traditional and advanced non-thermal technologies, food's physicochemical and sensory quality is affected to some degree due to mechanical, electrical, or other physical damage to the microstructures of the cell wall and cell membrane. Currently, the assessment of food quality has been focused on conventional physicochemical methods, biological indicators, and sensory analysis, which are destructive, time-consuming, and laborious (Ren et al., 2022). These techniques are considered targeted methods and are often used to measure one specific aspect or a single well-described attribute of a given food (ElMasry & Nakauchi, 2016). However, non-targeted methods that simultaneously enable the acquisition of information about several parameters are more appropriate for measuring food quality. A remarkable innovation has recently been seen in the application and use of non-targeted detection methods to determine and monitor food quality (Hassoun, Siddiqui, et al., 2022; Özdoğan et al., 2021). Most non-targeted methods are well adopted with the principle of non-destructive non-contact screening. The need for such techniques has been receiving even more interest over the past two years due to the outbreak of the ongoing COVID-19 pandemic and the increasing demand for less human contact with food (Khaled et al., 2021). Green foodomics and bioinformatics technologies, including metabolomics (e.g., chromatography–mass spectrometry-based metabolomics, and NMR-based metabolomics), have gained much attention (Balkir et al., 2021). Besides, image and spectroscopic techniques are becoming increasingly interesting alternatives to traditional methods, enabling rapid online measurements (Mahanti et al., 2022; McVey et al., 2021). These advanced analytical techniques have recently been empowered by the advent of the Fourth Industrial Revolution (Industry 4.0) technologies.

Industry 4.0 has emerged due to the fusion of multidisciplinary fields, particularly the digital, biological, and physical domains (Maynard, 2015). In the food industry, the ongoing Industry 4.0 era has been characterized by high interconnectivity and growing use of novel technologies, especially digital innovations, e.g., Artificial Intelligence (AI), cloud computing and analytics, and blockchain, and other emerging techniques, such as the Internet of Things (IoT), smart sensors, autonomous robotics, and 3D food printing (Bouzembrak et al., 2019; Chowdhury et al., 2022; Galvan et al., 2021; Hassoun, Aït-kaddour, et al., 2022; Hassoun, Siddiqui, et al., 2022). These advanced technologies have accelerated digitalization and automation in almost all sectors, including the food industry, enhancing rapid, online and in-site monitoring and intelligent food quality control. According to the Scopus database, the number of publications and citations related to digitalization or automation in food quality has increased tremendously in the last decade, and it is still permanently increasing (**Fig. 1**).

<**Fig. 1** near here>

Quality 4.0 concept has been used in many fields, such as development and management, organizational readiness, businesses, and leadership (Antony et al., 2021; Javaid et al., 2021; Sader et al., 2021). However, there is a gap in literature, as up to date, no application has been reported in the food industry or food-related fields.This work will introduce, for the first time,the "Food Quality 4.0" concept referring to the use of Industry 4.0 technologies (e.g., AI, Big Data, smart sensors, etc.) to determine food quality in the most efficient, rapid, and reliable manner. This literature overview will show through specific examples how the application of the Food Quality 4.0 concept will contribute to ensuring high food quality, saving time and labor, and increasing the efficiency of the food industry.

The main motivation of the study is to encourage more automation and digitalization in the food industry. More concretely, this review paper aims to i) adopt the concept of Quality 4.0 in the food industry; ii) define the main enablers of Food Quality 4.0; iii) promote wider applications of Industry 4.0 technologies in the food industry; and iv) help to automate and digitalize quality analysis in the food industry.

The organization of this manuscript is as follows: After the introduction, Section 2 gives a general overview of Industry 4.0 technologies and introduces the Food Quality 4.0 concept. Section 3 presents the most common traditional methods as well as emerging techniques and approaches used for the determination of food quality. Section 4 presents a short discussion, highlighting the main theoretical and practical implications of Food Quality 4.0 and its relevance to policy makers. The main conclusions, limitations, and future perspectives are briefly presented in Section 5.

This literature review was conducted with a methodology that focused on scientific articles authored in the English language, published in peer-reviewed journals in the last ten years. Data were obtained from Scopus with the following search criteria: Title, Abstract, Keyword; Food Quality AND Digitalization OR Automation.

2. Food Industry 4.0 and "Food Quality 4.0" concept

Industry 4.0 is gaining momentum and supporting businesses to optimize their operations by increasing automation and improving communication. It integrates recent developments in information technology, such as robotics and automation, Big Data, simulation, system integration, IoT, cybersecurity, the cloud, additive manufacturing, and augmented reality (Rüßmann, 2015), as shown in **Fig. 2**. In addition, Industry 4.0 can help increase the efficiency of operations by supporting the implementation of lean principles and methods, such as Just-in-time and Jidoka (Rosin et al., 2019).

<**Fig. 2** near here>

Industry 4.0 principles are related to the three pillars of sustainability (i.e., environmental, economic, and social domains). Ghobakhloo, (2020) analyzed such relationships and concluded that Industry 4.0 is more connected to the economic domain of sustainability, mainly through production efficiency and business model innovation. However, such principles can also pave the way for improvements in the environmental and social domains. Bai et al.,(2020) ranked Industry 4.0 technologies based on their impact on sustainability performance and placed mobile technologies first overall, while simulation ranked first in the food and beverage sector. Such technologies contribute unequally to the economic, environmental, and social dimensions of sustainability.

Although the implementation of Industry 4.0 technologies is generally expected to generate industrial benefits, some of these technologies are still at a very early stage of adoption. As a result, they do not offer clear benefits yet, especially in emerging economies (Dalenogare et al., 2018). In this context, Raj et al.,(2020) analyzed the barriers to adopting Industry 4.0 technologies in the manufacturing sector of developed and developing economies. They found that, although the lack of a digital strategy alongside resource scarcity is the most significant barrier in both types of economies, important differences exist between developed and developing countries. In developing countries, improvements in standards and government regulation could facilitate the adoption of Industry 4.0 technologies, whereas the focus should be on technological infrastructure in developed countries. An important challenge to implementing Industry 4.0 more widely is the lack of expertise and thus the need for a skilled workforce to operate such new systems (Sony & Naik, 2020).

The adoption of Industry 4.0 technologies varies significantly among European countries. The Netherlands and Finland are leading the implementation thanks to their Industry 4.0 infrastructure and Big Data maturity, while Hungary, Bulgaria, and Poland rank last (Castelo-Branco et al., 2019). Sony & Naik, (2020) proposed factors from the following themes to assess Industry 4.0 readiness for businesses (**Fig. 3**).

<**Fig. 3** near here>

Macroeconomic factors also influence the adoption of Industry 4.0, such as the structure of the industrial sector, its role within each country's economy and differences in business models or management styles (Castelo-Branco et al., 2019). Frank et al.,(2019) proposed a framework to support the implementation of Industry 4.0 technologies in manufacturing businesses.

Food businesses are slowly embracing Industry 4.0 technologies, with sensors, simulations, AI-based autonomous systems, additive manufacturing, cloud systems, and blockchain projected to have the greatest impact in the sector. There are several examples of the application of such technologies in various food-manufacturing applications, such as logistics (Jagtap, Bader, et al., 2021); reduction of waste, energy and water use (Jagtap, Garcia-Garcia, et al., 2021); data collection and monitoring (Konur et al., 2021a); and quality control (Garcia-Garcia et al., 2021).

Currently, Quality 4.0 is integrated with traditional quality practices rather than substituting them (Sader et al., 2021). According to interviews with senior management professionals, the most critical technologies for driving Quality 4.0 are predictive analytics, sensors and tracking, and electronic feedback loops (Antony et al., 2021). Nevertheless, it is often difficult to transform traditional quality-control processes into Quality 4.0 and obtain value from such changes. Therefore, Escobar et al.,(2021) presented a problem-solving strategy based on seven steps (namely, identify, accessorize, discover, learn, predict, redesign, and relearn) to increase the likelihood of success in implementing Quality 4.0.

Quality control is key in the food sector, as it assures food products are safe for consumers and have the required organoleptic properties. Quality 4.0 allows assessing the quality of food products more accurately and in real-time (Ada et al., 2021), thus facilitating traceability (Khan et al., 2020), which is a critical step toward more transparency in the food supply chains. There already exist examples of the application of Quality 4.0 to optimize the quality-control process in food businesses. Bhatia & Ahanger, (2021) presented an IoT-based framework to assess food-quality parameters in restaurants and food outlets. Rejeb et al., (2020) analyzed the implementation of blockchain technology for different applications, including quality assurance in the food supply chain. Ping et al., (2018) reviewed the application of IoT technology in monitoring agricultural product's quality and safety.

Furthermore, due to the high perishability of food products, smart packaging plays an important role in food quality to extend the shelf life, improve quality, safety, and provide information about food products. Technologies integrated into smart packaging include nano sensors, biosensors, and gas sensors to measure the temperature and freshness of food products (Ben-Daya et al., 2020).

Implementation of Industry 4.0 technologies could create huge time and cost savings compared to traditional analytical approaches. Although initial capital investment associated with innovative technologies could be large, higher product quality, fewer errors, and reduced machine downtimes,and other desirable features associated with smart technologies make the move from traditional to Quality 4.0 system financially viable. For example, the application of blockchain will not only solve problems of food safety and quality and improve transparency but also reduce costs along the different stages and operations of food supply chain, such as transaction, quality, and time costs, among other costs (Qian et al., 2022; Xu et al., 2020). Beside economic costs, a wider implementation of digitalization, AI, and other Industry 4.0 elements has high potential to reduce environmental costs by supporting the transition towards more sustainable food systems (Marvin et al., 2022). Despite these advances, most of the innovative technologies are still under development, and further research and testing is still required to accelerate the transitionfrom laboratory to industrial-scale applications.

In conclusion, Industry 4.0 technologies show great potential for food businesses. Industry 4.0 may optimize the quality-control process, key in the food sector, by increasing automation and digitalization, and improving communication. The rest of the article reviews traditional methods used to determine food quality and emerging techniques within Quality 4.0 that are expected to contribute to the development of quality control in the food sector in the coming years.

3. Findings

3.1. Traditional methods used for the determination of food quality

Quality is defined through various characteristics, including nutritional value, physicochemical properties, safety, sensory attributes, and shelf-life stability. Several standard and reference methods have been used over the years to determine the quality and authenticity of food products, mainly based on intrinsic attribute measurements (Bernués et al., 2003; Kutsanedzie et al., 2019). Among them, physicochemical determinations (color, texture, water holding capacity) that are related to product technological properties, sensory attributes (flavor, juiciness, tenderness) linked to consumer acceptability, safety aspects including the presence of pathogenic and foodborne microorganisms or toxic substances, and nutritional/health concerns (proximate composition, fatty acid and amino acid composition) are included among these analytics (Lorenzo et al., 2022).

The most commonly used methods are supported by international organizations such as the AOAC International, International Organization for Standardization (ISO), or the American Oil Chemists Society (AOCS) (AOAC, 2019; ISO, 1981). The standards are intended to establish a quality system, maintain product integrity, and satisfy customers. Others, such as *Codex Alimentarius* also aim to protect consumers' health and guarantee and facilitate international food trade. In addition, these methods allow the comparison of results, ensuring that the results are of quality.

There is no single standard method for proximate composition determination since the selection of the method depends on the type of sample. This is clearly reflected in the case of lipids, where the total content could be quantified by organic solvent extraction methods such as Soxhlet or Folch, among others. In the case of protein, Kjeldahl and Dumas methods based on nitrogen measurements are commonly used. In the case of total carbohydrate analysis, colorimetric and reducing sugar methods are applied, while gravimetric procedures are the ones selected in the case of moisture and ash. Moreover, spectroscopic methods are based on the absorption or emission of radiation in UV-visible, and infrared frequency ranges are among the common instruments in many food laboratories. In fact, these analyses can also be carried out using near-infrared reflectance spectroscopy (NIRS), which allowsthe detection of product adulterations, predicting fat, protein and water content quickly. Still, it has some limitations regarding instrument calibration and spectra interpretation (Troy et al., 2016). In addition, the high absorbance of the NIRS signal by water could disturb the results in products with high moisture content (Liu et al., 2015). In elemental analysis, atomic emission spectroscopy (AAS), flame atomic emission spectroscopy (FAAS), inductively coupled plasma-atomic emission spectrometry (ICP-OES) are among the recommended techniques. In contrast, various chromatographic and mass spectrometry techniques are used to identify these compounds in a more specific way (Di Stefano et al., 2012). **Fig. 4** shows the traditional methods *vs.* emerging techniques for food quality determination.

<**Fig. 4** near here>

Regarding physicochemical parameters, color is one of the most important parameters that has a huge impact on consumer acceptance, and is especially important in products, such as meat and meat products, oils, or honey, among others (Brühl & Unbehend, 2021; Kuś et al., 2018; Milovanovic et al., 2020; Tomasevic et al., 2019). It can be evaluated using visual or instrumental methods. In the first case, color pattern cards or photographic scales are used. However, visual evaluation is considered a subjective measure, since it is dependent on several factors, such as testing conditions, lighting, color tones, training of assessors, and difficulty in finding matches between standards and tested samples. In the case of instrumental measurements, the evaluation based on the CIELAB system allows determining the exact color of the product in a three-dimensional color sphere through the determination of three coordinates defined as L^* (luminosity), a^* (redness-greenness), and b^* (yellow-blueness). Moreover, other parameters such as chroma (C^*) and hue (h^*) can also be obtained from a^* and b^*.

Food texture is another determining characteristic in food products since it conditions food satiety, the organoleptic experience of the consumer, and the overall acceptance of food products (Guimarães et al., 2020). Sensory, instrumental (known as objective, physical or mechanical) and indirect methods (collagen content, dry matter, among others) can be used to evaluate texture. The main textural parameters evaluated in instrumental methods are hardness and cohesiveness, although springiness, gumminess, and chewiness are also evaluated. These parameters are selected depending on the product to be analyzed. The most common way to determine these parameters is mechanical tests, such as the Warner-Bratzler test (WB) and texture profile analysis (TPA). However, other parameters are more difficult to determine through instrumental methods. It is the case of adhesiveness, creaminess, tenderness, and juiciness since these characteristics are more linked to oral processing (Pascua et al., 2013). Therefore, they are usually evaluated through sensory assessment. Consequently, many industries use both methodologies since they are complementary and provide more reliable results. Along with these, the rheological properties of foods are also determined to determine how the shape of the food changes in response to some applied force. Other physicochemical parameters such as acidity or electrical conductivity could complement the previous determinations, and in some cases, they would offer important data about their quality.

In the case of microbiological analysis, there are several methodologies to determine the viability of a product and the identification of microbial contaminants. However, cultivation continues to be the most widely used method. It is the case of Total Viable Counts (TVC) determination, considered as a standard tool (Hassoun, Gudjónsdóttir, et al., 2020). In addition to this, enzyme-linked immune sorbent assay (ELISA) and polymerase chain reaction (PCR) are commonly used. Other parameters can also be used as freshness indicators, along with these determinations. This is the case of peroxide values (PV) and thiobarbituric acid reactive substances (TBARS), or protein carbonyls and total volatile basic nitrogen (TVB-N), which are related to the stability of, respectively, lipids and proteins to oxidation (Bekhit et al., 2021; Domínguez et al., 2019; Rubén Domínguez et al., 2022).

The value of these analytics is unquestionable, but the results of these techniques must be correlated with sensory analysis since the results obtained in the sensory characterization of a product are of vital importance both in the development of new products and in their acceptance by the final consumer (Ruiz-Capillas et al., 2021). Descriptive sensory analysis is the most usedmethod in sensory characterization. The attributes are evaluated by a panel of highly trained panelists, making the results obtained more objective and reliable. This, together with the fact that it is a flexible method, has continued to be used over time (Purriños et al., 2022). The selected attributes usually offer a large amount of information about the product whose intensity is evaluated within a structured scale (Pateiro et al., 2022).

In summary, there are many methods conventionally used to determine food quality. However, it is important to note that although they have good precision and reliability, in many cases, they require several preliminary steps, are destructive, and are time-consuming (Hassoun et al., 2019), highlighting the urgent need for more innovative and advanced analytical approaches.

3.2. Emerging techniques and approaches

3.2.1. Non-destructive fingerprinting techniques

As discussed before, conventional or traditional methods used to determine food quality have several drawbacks, e.g., laborious and destructive nature, high cost, long process time, a limited number of analytes, and low performance (El-Mesery et al., 2019; Khaled et al., 2021; Sarkar et al., 2022; Valdés et al., 2021). These drawbacks can be faced by the Industry 4.0 vision or Quality 4.0 principles. Non-destructive, non-targeted fingerprinting methods (e.g., spectroscopic and imaging techniques) can be more suitable for analyzing complex materials such as food products, achieving rapid and cost-effective outcomes. Moreover, the need for such non-destructive methods has become more evident in the last two years due to the outbreak of COVID-19 and the trend of increased adoption of automation and AI in the food industry (Khaled et al., 2021).

This section will discuss a selection of the most common non-destructive fingerprinting techniques. Spectroscopic techniques are based on the interaction between electromagnetic radiation and matter at various wavelengths. Spectroscopic-based techniques can provide reliable information about physical properties and the chemical composition of samples quickly and inexpensively, in line with the core principles of Quality 4.0. A range of spectroscopic techniques, including, among others, near-infrared (NIR) and mid-infrared (MIR) spectroscopy (Munawar et al., 2022; Pasquini, 2018; Su & Sun, 2019), fluorescence (Hassoun, 2021; Hassoun et al., 2019), and Raman spectroscopy (Jiang et al., 2021; Lintvedt et al., 2022), has recently been gaining special attention due to their desirable features such as high sensitivity and specificity and the possibility of being applied on line during food production or processing for real-time data acquisition of intact samples.

Spectroscopic methods have been widely used in many applications, ranging from detection of adulteration and fraud (Hassoun, Måge, et al., 2020; Hassoun, Shumilina, et al., 2020; Rifna et al., 2022; Silva et al., 2022; Zaukuu et al., 2022), determination of the chemical composition or specific constituents (Xu et al., 2022), monitoring processing conditions, such as thermal and non-thermal treatments (Abderrahmane Aït-Kaddour et al., 2021; Hassoun, Ojha, et al., 2020; Hassoun et al., 2021; Hassoun, Heia, et al., 2020), to the determination of food quality and safety (Fan et al., 2022; Hassoun & Karoui, 2017; Wang et al., 2018; Wu et al., 2021).

In recent years, tremendous progress has been made in miniaturized instrumentation, compact spectral sensors and handheld systems (Giussani et al., 2022; Müller-Maatsch et al., 2021; Müller-Maatsch & van Ruth, 2021; Rodriguez-Saona et al., 2020) has been made, driven by Industry 4.0 innovations and recent advancements. This trend has especially concerned NIR spectrometers that have become available at a much smaller size and lower cost than traditional NIR benchtop laboratory instruments (Beć et al., 2021; Giussani et al., 2022). Furthermore, the integration of AI, deep learning, smart sensors, and other Industry 4.0 elements into spectroscopic systems has enhanced the analytical performance of the proposed analysis systems. For example, in a recent study, a portable system integrating NIR sensor, load sensor, and deep learning methods was proposed for mixture powdery food evaluation (Zhou et al., 2022).

One of the most significant communication protocols for Industry 4.0 and IoT is Open Platform Communications Unified Architecture (OPC-UA). OPC standardizes access to machines, devices, and other systems in the industrial environment, allowing for identical and manufacturer-agnostic data sharing (Ioana & Korodi, 2021). For example, a miniaturized spectrometer technology, combined with AI was developed (called SmartSpectrometer) and used to predict sugar and acid in grapes in the field. The open communication interface OPC-UA can be used to connect the SmartSpectrometer modules on one side by ensuring interoperable data and information sharing inside and on the other side between different Industry 4.0 automation levels. Production processes can be optimized, quality can be improved, and resources can be saved by collecting and analyzing spectroscopic measurement data and exchanging production-relevant information (Krause et al., 2021).

Hyperspectral imaging (HSI) combines traditional spectroscopy and imaging and simultaneously obtains spectral and spatial information. HSI has been most commonly used in Vis/NIR, fluorescence, and Raman (Özdoğan et al., 2021; Qin et al., 2020). Three different sensing modes, namely interactance, reflectance, and transmittance, are widely applied for various applications (Hassoun, Heia, et al., 2020; Khaled et al., 2021; Ma et al., 2019). The technique can also be used with microscopy systems (Pu et al., 2019). Data created by HSI has a three-dimensional structure; x, y, λ (called hypercube), with two spatial dimensions (x rows, y columns) and one spectral dimension (a range of wavelengths).A detailed overview of HSI principles, different configurations and settings, and various hardware and software can be found in other review papers (Caporaso et al., 2018; Fu & Chen, 2019; Ma et al., 2019; Wang et al., 2021).

HSI was first used in remote-sensing applications, but the range of applications has recently become very large, including food quality (Caporaso et al., 2018; Pu et al., 2019; Saha & Manickavasagan, 2021). HSI can be used to evaluate external quality attributes and internal quality parameters (Hassoun et al., 2021; Khaled et al., 2021; Ma et al., 2019; Wang et al., 2021). HSI is most used in sensory and freshness assessment (Özdoğan et al., 2021), authentication (Qin et al., 2020), and determination of the quality of different food categories such as egg (Yao et al., 2022), meat (Fu & Chen, 2019), and fruits and vegetables (Lu et al., 2017). Recent research has shown that most of the quality indicators (discussed in Section 3), such as TVB-N, TBARS, TPA, and color, can be predicted from HSI data. Some relevant examples of recent applications of HSI in the field of food quality control can be found in **Table 1**. This table shows that HSI has been widely used in various food products, mostly of animal origin, and the Vis/NIR range (especially 400-1000 nm) has been the most used mode.

<Table 1 near here>

Compared to other techniques, HSI has many desirable features that meet Industry 4.0 requirements. The technique is characterized by high speed, accuracy, automation, and real-time monitoring and could be suitable for automated quality evaluation and safety inspection of large sample sets. Although most investigations have been conducted at the laboratory level, HSI has great potential for industrial applications (El-Mesery et al., 2019; Lu et al., 2017; Özdoğan et al., 2021). One of the main limitations of HSI remains the huge amount of obtained data that should be processed in real-time. However, with the rapid developments in technology (especially the recent advancements of Industry 4.0 and the combination of HSI with Big Data and cloud-computing technologies), the development of new algorithm models for optimal wavelength selection and implementation of multispectral imaging have enabled higher computing efficiency and enhanced the entire system performance, demonstrating the feasibility of using HSI to evaluate numerous properties of various food products (Khaled et al., 2021; Ma et al., 2019; Özdoğan et al., 2021).

Besides spectroscopic and imaging techniques, a wide range of analytical methods have been developed in recent years. These include acoustic and ultrasound sensing (Caladcad et al., 2020; Lei & Sun, 2019), machine vision system and computer vision (El-Mesery et al., 2019; Kakani et al., 2020; Saberioon et al., 2017), bioelectrical impedance analysis (Fan et al., 2021; Huh et al., 2021), wireless chemical sensors and biosensors, such as radio-frequency identification (RFID) (Karuppuswami et al., 2020; Kassal et al., 2018), electronic nose and electronic tongue (Di Rosa et al., 2017), just to mention a few. However, most of these techniques are still under development and require more research to meet industrial needs.

3.2.2. Omics and bioinformatics technologies

Generally, foods represent very complex and diverse mixtures consisting of naturally occurring compounds including primary and secondary metabolites such as lipids, proteins, carbohydrates, amino acids, fatty acids, phytochemicals, colorants, aromas, preservatives, among others, in addition to several other exogenous compounds, which pose enormous analytical challenges. The assessment of these metabolites and the monitoring of food quality and food safety imply the use of robust, sensitive, cost-effective, and efficient analytical methodologies.

Currently, the most common high-throughput analytical techniques that are well accepted and taken as gold standards for food quality assessment and safety monitoring are liquid (LC) or gas chromatography (GC), usually coupled to mass spectrometry (MS), nuclear magnetic resonance (NMR) spectroscopy, and capillary electrophoresis (CE) (**Fig. 5**).

<**Fig. 5** near here>

In addition to those molecular analysis methods, other methodological approaches of biological origin, such as ELISA and PCR, are also used extensively in food analysis (Tramuta et al., 2022; Xu et al., 2022). Although these methods have been in use for a long time (hence their introduction in Section 3), recent advances and developments in terms of instrumentation and techniques have revolutionized many aspects of analytical chemistry. Coupled with machine learning, these techniques are a promising way of modelling food-human interaction. In recent years, bioinformatics technologies have been gaining popularity, especially with the increased need for enhanced computational capabilities to process huge biological data, enabling effective monitoring of food quality (Jeevanandam et al., 2022). Omics is a sub domain of "foodomics" that studies food and nutrition domains through the application and integration of advanced omics technologies, such as proteomics (proteins), metabolomics (metabolites), and genomics (detection of genes), among others (Balkir et al., 2021; Carrera et al., 2020; Picone et al., 2022).

One of the most powerful analytical techniques that has played a vital role in food safety and quality issues, in addition to food authenticity and labeling accuracy as a useful tool to prevent food fraud and adulteration, is liquid chromatography with ultraviolet (LC-UV) detection or coupled to mass spectrometry (LC-MS) (Malik et al., 2010; Núñez et al., 2005).The characterization of food products based on LC analytical methodologies has been reported in several works, providing a large amount of information, such as the confirmation and quantification of thousands of compounds in one chromatographic run (Núñez et al., 2005). For example, native Colombian fruits and their by-products were characterized by Loizzo et al., (2019) by determining their hypoglycemic potential antioxidant activity and phenolic profile. The presence of chlorogenic acid as a dominant compound in Solanaceae samples was revealed by ultra-high performance liquid chromatography-high resolution mass spectrometry (UHPLC-HRMS) with an Orbitrap mass analyzer. Izquierdo-Llopart & Saurina, (2019) established the polyphenolic profiles (280, 310 and

370 nm) of sparkling wines by LC-UV/Vis and principal component analysis (PCA). Figueira et al., (2021) established the fingerprint of the free low molecular weight phenolic composition and bioactivity of *Vacciniumpadifolium* Sm. fruits by LC-MSMS, while Aguiar et al., (2020) reported the chemical fingerprint of free polyphenols and antioxidant activity in dietary fruits and vegetables using a non-targeted approach based on QuEChERS-ultrasound assisted extraction combined with UHPLC-FLR.

In a recent study, Reyrolle et al.,(2022) selected ion flow tube mass spectrometry (SIFT-MS)was developed to detect and quantify volatile organic compounds emitted by ewe cheeses, illustrating producer's typicality and process control and the impact of the animals' diet on the final product without any previous separation step. Other applications of chromatography and spectrometry techniques for the analysis of food metabolites and metabolomics research have been recently reviewed (Emwas et al., 2021; Pedrosa et al., 2021).

NMR is a non-destructive analytical method based on the magnetic properties of several atomic nuclei, in which the spin nuclear magnetization of a sample that contains NMR active nuclei and is located inside a strong field NMR magnet, is excited by radio-frequency pulses generating a signal, which during its relaxation back to equilibrium, is recorded and Fourier transformed to provide the NMR spectrum. The most common nuclei studied in food analysis are hydrogen, deuterium, carbon, and phosphorus (Higashi et al., 2020; Pedrosa et al., 2021; Wieczorek et al., 2021). NMR is well suited to omics approach. It is a versatile and accurate quantitative technique that can be applied to samples of all states of matter for quality control, production monitoring/improvement, sensory evaluation, and food authentication. However, its sensitivity is relatively low compared to other high-throughput technologies. High-resolution solid state (Munson et al., 2022) and liquid state NMR (Dubrow et al., 2022) are the most common NMR techniques applied to food to obtain a frequency domain spectrum.

CE is another emerging technique that has generated great interest in the analyses of many compounds due to its high separation efficiency, extremely small sample and reagent requirements, and rapid analysis. Recently, Valdés et al., (2022) presented a detailed overview of the main applications (e.g., detection and analyzing carbohydrates, amino acids, biogenic amines, heterocyclic amines, lipids, proteins and peptides, vitamins, among others)of CE methods in food analysis and foodomics. Another review paper provided an overview of the application of MS, NMR, CE and other metabolomics approaches for the characterization of meat and the exploration of biomarkers in the production system (Muroya et al., 2020).

Despite the numerous obvious advantages and the important capabilities and possibilities offered by the application of omics and bioinformatics, these main characteristics of the Quality 4.0 era are not without challenges. The main obstacles are the complexity and variety of data generated from different bioinformatics tools, expensive instrumentation, and lack of skilled operators needed for method development (Valdés et al., 2021, 2022).

3.3. Artificial Intelligence (AI) and Big Data

Industry 4.0 includes innovative technologies, such as Big Data and AI. Deep learning and Big Data are among the most important topics of Industry 4.0 (Zeba et al., 2021). These technologies exist within smart ecosystems: humans, machines, and devices interact for efficient product manufacturing. These technologies improve food manufacturing efficiency and consistency and reduce operational costs. They may be implemented to adapt existing machinery to a new way of operating instead of expensive replacement (Konur et al., 2021b). Integrating Big Data and AI into traditional food science can create new recipes alongside intelligent recommendations, track and trace food for improved food quality, and analyze food taste preferences.

3.3.1. Agriculture

Agri-food supply chains are the source of quality raw materials transformed into quality manufactured foods. In response to consumer demand for affordable and higher quality food, agri-food supply chains deploy AI and Big Data to guide decision-making to improve food product quality through traceability, reduced waste and improved productivity. For example, AI can assess plants and fruits at various harvest stages and post-harvest stages to detect effects such as decay and mold (Stasenko et al., 2021). There are, however, challenges to the digitalization of agri-food supply chains such as low inter-operability of different data sets, silo mentality, low willingness to share data and a significant skills gap (Serazetdinova et al., 2019).

Our ability to assess crop quality at scale in the fields has recently improved due to remote sensing and AI, which integrate Big Data into predictive and prescriptive management tools to address agricultural and human nutrition challenges (Jung et al., 2021). AI has great potential to support the transition to sustainable food systems, impacting the entire value chain from farmers to consumers (Marvin et al., 2022). AI may be combined with ontological models to improve the product quality of vertical farms, supporting autonomous data-driven decisions (Abbasi et al., 2021). Further optimization and decision-making support may be derived from digital twins that rely on AI and Big Data for even greater insights (Nasirahmadi & Hensel, 2022).

3.3.2. Traceability

Food traceability is an important means of ensuring food quality that addresses trust issues between consumers and the market. RFID technology and Big Data may be used to obtain information about the food production process (Zheng et al., 2021). Processed food is particularly challenging due to the variety of raw materials, batch mixing and resource transformation. In the context of processed food, AI may be used to optimize batch mixing and Big Data can support quality forecasting (Qian et al., 2022). It is predicted that blockchain technology will be integrated with AI and Big Data, supporting a new level of supply chain traceability.

3.3.3. Food processing quality

With respect to food processing, AI-based 3D food printing can produce high quality, customized products for individuals based on appropriateness judgments and standards for food ingredients supported by Big Data values of various food groups (Yoo & Park, 2021). Furthermore, new food product development can look to "computational pharmaceutics" (Wang et al., 2021) for inspiration on integrating Big Data, AI and multi-scale modelling techniques for pre-formulation studies and predicting nutritional effects. Recently, AI used in conjunction with simple sound vibrations traversing the food product has demonstrated the ability to verify high-quality products with no additives and organic food products (Iymen et al., 2020).

3.3.4. Sensors and food quality

Determining the quality of a food product may also be aided by sensor data combined with AI and Big Data. Non-destructive spectroscopic, acoustic, ultrasound and artificial sensing techniques have immense food quality testing applications. The application of computer vision and learning methods to improve the food industry is termed "computer vision and AI-driven food industry" (Kakani et al., 2020).

Biogenic amines are important biomarkers for monitoring food quality that benefit from AI's application; this application may be a new way to monitor the freshness of meat (Tan et al., 2022). Non-destructive inspection based on X-ray CT scans has been used with a deep neural network to indicate suboptimal storage conditions of pear fruits. In addition, the technique can be used to detect internal disorders, such as internal browning and cavity formation, which are often invisible from the outside (Van De Looverbosch et al., 2021).

Nonthermal technologies such as high-power ultrasound, pulsed electric fields, high voltage electrical discharge, high-pressure processing, UV-LED, pulsed light, e-beam, and advanced thermal food processing techniques including microwave processing, ohmic heating, and high-pressure homogenization may all benefit from the implementation of smart sensors combined with AI and Big Data (Jambrak et al., 2021). AI may support food quality analysis using food images (from smartphones) to estimate their nutrient content (Ma et al., 2022). In addition, AI human-like sensors exist for vision, hearing, smell, taste and touch (Zhao et al., 2020), which may complement and eventually replace human sensory tests of food quality.

Big Data and AI afford opportunities for multi-parameter sensing that mimics the sense of taste, overcoming the limitations of salty, sweet, sour, bitter and glutamate sensing by using electronic taste chip systems that can act as fingerprints of health and wellness (Christodoulides et al., 2019). In addition, E-sensing and nanoscale-sensing devices may be combined with AI for food quality control (Galvan et al., 2021)(Galvan et al., 2021)[20](Galvan et al., 2021). However, although there is significant literature investigating food product quality with computer vision algorithms, there is a lack of commercial exploitation (Meenu et al., 2021).

3.3.5. Food safety and food quality

The globalization of food production makes ensuring food quality more difficult. Therefore, a reliable digital ecosystem of food quality management requires a balanced strategy for the integration of Big Data, AI and blockchain for the end-to-end monitoring of food quality and safety and improvement of quality management and traceability of food products at all stages – production, circulation and consumption (Savina et al., 2020).

3.3.6. Food supply chain and cold chain

The main challenge of Sustainable Development Goal 12, "Responsible Consumption and Production", is the reduction of food losses along production and supply chains. Improving food product quality is particularly important for fresh food products to avoid waste and losses. Big Data and AI may bring new solutions to mitigate the perishability nature of fresh food products (Vernier et al., 2021).

Constructing a traceable system for cold chain logistics would help brand image and increase consumer trust by delivering safe and higher-quality food products (Wang et al., 2020; Zhuangzhuang, 2020). Traditional systems may be slow to adjust the fresh food storage temperature. Temperature control algorithms using AI and Big Data may be used to adjust the temperature environment so that food is consistently at the optimal storage temperature (Guan et al., 2021).

3.3.7. Packaging

Food quality depends on food packaging methods and materials. AI and Big Data can be used to assess a range of environmental factors near food manufacturing sites and impacts within a variable food packaging value chain for better decision-making on packaging materials aligned with the Sustainable Development Goals (Sand, 2020). Furthermore, recent advances in nanotechnology have enabled the development of small devices and nano-sized sensors that could be incorporated in food packaging or even in smartphones giving consumers the ability to assess the quality and investigate the properties of their own food easily (Saadat et al., 2022).

4. Discussion and implications

Our literature overview revealed that some of the recently developed technologies can be considered promising options in food quality assessment. Specifically, the use of spectroscopic techniques (NIR, MIR, fluorescence, and Raman spectroscopy) in addition to HSI has received much attention in the determination of food quality. For example, the HSI technique generates both spectral and spatial data, showing promising results for various classification purposes and prediction of many traditional quality parameters (e.g., TVB-N, TBARS, TPA, and color). Imaging and spectroscopic techniques have demonstrated considerable capacity to detect food fraud and determine chemical composition, food quality and safety parameters, as well as monitor particular quality parameters during production, processing, or storage of food. Most of these techniques are non-destructive, relatively low-cost, and generate data that contains maximum information, providing a "fingerprint" of the investigated food product. Other analytical methods, such as mass spectrometry and chromatographic methods are powerful tools to determine freshness parameters, safety, authenticity, traceability, and overall quality of foods, but they often require large equipment and experienced laboratory personnel.

Recently, "omics" has emerged as a sub-domain of "foodomics" that refers to the study of proteomics (proteins), metabolomics (metabolites), among others, through the application of advanced platforms of electrophoresis, molecular approaches, nuclear magnetic resonance spectroscopy, and others (Creydt & Fischer, 2018; Singh et al., 2021). More recently, food quality monitoring through bioinformatics, Big Data, machine learning, AI, IoT, and smart sensors has received huge considerations (Bouzembrak et al., 2019; Goyal et al., 2022; Jagatheesaperumal et al., 2021; Jeevanandam et al., 2022; Kumar et al., 2021; Marvin et al., 2022; Mavani et al., 2021). These Industry 4.0 elements have revolutionary features (e.g., allowing obtaining robust data, appropriate for real-time measurements, and saving time and costs), making them most suitable for the future Food Quality 4.0 era.

Our findings highlight the importance of AI and Big Data as a crucial pillar of Food Quality 4.0 era. The use of these digital quality enablers in agriculture, traceability, food processing quality, packaging, and other stages along the supply and cold chains has been demonstrated through concrete examples. However, the findings from our review shows that research studies dealing with the application of Industry 4.0 technologies in the food industry are limited. This is likely due to the silo mentality and the conservative nature of the food industry compared to other industrial sectors (Chapman et al., 2022; Hassoun et al., 2020), in addition to other limitations that will be discussed in the next section.

The introduction of Quality 4.0 concept into the food industry could have several theoretical and practical implications. Theoretically, the incorporation of Food Quality 4.0 will address the gap highlighted in the literature regarding the scarce of research investigating application of Industry 4.0 technologies in the food industry. Food Quality 4.0 opens up promising avenues for future research in several digitalization and automation technologies. Although, most of the topics discussed in this work were previously reviewed in more detail in other publications, to the best of our knowledge, this manuscript is the first to raise awareness of the importance of multidisciplinary approaches and simultaneously considering a wide range of emerging technologies that address the key principle of Industry 4.0, namely the convergence between various areas of science, especially physical, biological, and digital disciplines.

In practice, this research can be used as a basis for understanding the different challenges and opportunities offered by adopting Quality 4.0 in the food industry. More adoption of Quality 4.0 enablers will ensure best quality management practices of raw materials and final food products during production, processing and commercialization. Close collaboration and cooperation between different actors is needed to optimally implement and fully exploit and harness the potential of Industry 4.0 in food quality.

5. Conclusions, limitations, and future research perspectives

The main objective of this work is to discuss the concept of Food Quality 4.0, highlighting the potential of emerging analytical methods and smart technologies, in the context of the Fourth Industrial Revolution (Industry 4.0), for enhancing food quality. Industry 4.0 technologies have a significant role to play in sustainable social, environmental, and economic development. Although the Quality 4.0 concept has been used in many other disciplines, such as manufacturing development, management, and related fields (Antony et al., 2021; Javaid et al., 2021; Sader et al., 2021), up to date, an obvious gap in literature can be noticed since no application has been reported in the food industry. This review paper provides an up-to-date source of information about the latest developments and advances in food quality assessment methods by introducing, for the first time, the concept of "Food Quality 4.0" in food-related applications.

The results of this review may help policy makers to move toward fostering and supporting transdisciplinary collaboration to embrace more technological innovations. Long-term policy-making strategies are needed to facilitate the adoption of the Industry 4.0 paradigm, and consequently accelerate the implementation of Food Quality 4.0. The results of our literature review show that, despite the increased research attention directed to the importance of Industry 4.0 technologies, there are a lot of uncertainties regarding the wider adoption of these technologies in the food industry. There is still a lack of serious awareness related to Industry 4.0 features within the food quality context. However, the interest for Industry 4.0 among managers and policy-makers has increased significantly in recent years. Managers and policy-makers should set out on a journey towards Food Quality 4.0 by identifying the measures (such as incentives, roadmaps, and consultancy services) that could facilitate the implementation of Industry 4.0 technologies in small and medium-sized enterprises (Matt et al., 2020). The role of new generation (young managers and leaders) having an open-mindset should be strengthen and prioritized in decision-making process to overcome the limitation of silo mentality, which is a well-known character of food industry.

The efficiency of food quality and safety assessment methods, as well as food processing technologies come into question with every food crisis and pandemic outbreak, seriously undermining consumer confidence. The role policy makers is particularly important during crises, such as the coronavirus pandemic. For this reason, it is ever more important, during and in the wake of the COVID-19 pandemic, to develop rapid and non-destructive techniques to measure food quality efficiently and objectively.

Food quality is traditionally determined using intrinsic attributes, such as physical, chemical, microbial, and technical (processing) parameters, through the application of numerous methods that are time-consuming, laborious, and destructive. In contrast, Industry 4.0 technologies have strong prospects for overcoming these limitations. By combining the physical, digital, and biological worlds, Industry 4.0 has recently begun to automate and digitalize many food production and consumption sectors thanks to the implementation of AI, Big Data analytics, IoT, smart sensors, robotics, and other digital and innovative technologies along the whole food value chain. Industry 4.0 innovations and technologies can be employed to enable Food Quality 4.0, improving efficiency, rapidity, and reliability of food assessment techniques.

A successful transition from the traditional to Food Quality 4.0 system implies some prerequisites and challenges that need to be addressed. While Food Quality 4.0 offers various advantages concerning automation and digitalization in food quality analysis, it faces various obstacles. The techniques need to be more affordable, adequate in size, and efficient in industrial environments. High cost, lack of adaptability to the existing industrial environment, and lack of technical skills are among the most challenging bottlenecks hindering the wider application of these technologies. Inadequate infrastructure facilities, especially in developing countries are also a critical limitation that needs to be addressed.

Besides the challenges related to implementation of Quality 4.0 concept and obstacles facing the application of emerging technologies, some limitations linked to the approach used in this review paper can be highlighted. Although most relevant studies (mainly extracted from Scopus) have been reported, more systematic reviews that consider bibliometric approaches to visualize results should be conducted in the future. A larger source of data, including, in addition to Scopus, Web of Science, Google Scholar, and other online databases (e.g., IEEE Explore, SAGE Publications, and MDPI, among others) should be considered.

However, in line with the ongoing efforts put into the development of technical innovations and digital solutions, it is expected that the limitations of these emerging techniques will be overcome. More research is needed to better understand the contribution of Industry 4.0 technologies to Food Quality 4.0. Optimal quality monitoring (once achieved by implementing Food Quality 4.0 principles) means smart quality controls and high-quality assurance of food products, reduced food waste and loss, and decreased use of resources and energy, thus enhancing the transition towards more sustainable food systems.

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Author Contributions

Abdo Hassoun: Conceptualization, methodology, writing—original draft preparation, revision, editing. Sandeep Jagtap, Guillermo Garcia-Garcia, Hana Trollman, Mirian Pateiro, José M. Lorenzo, Monica Trif, Alexandru Rusu, Rana Muhammad Aadil, Vida Šimat, Janna Cropotova: writing—original draft preparation, revision. José S. Câmara: writing—original draft preparation, revision, supervision, Review & Editing.All authors have read and agreed to the published version of the manuscript."

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Figure Captions

Fig. 1. Number of publications and citations per year (until June 06, 2022) related to the application of digitalization and automation in the food quality.

Fig. 2. Building blocks of Industry 4.0.

Fig. 3. Some factors to assess Industry 4.0 readiness for businesses.

Fig. 4. Traditional methods *vs.* emerging techniques used in the food quality determination**. Legend:** IRMS: Isotope Ratio Mass Spectrometry; MALDI-TOF-MS: Matrix-Assisted Laser Desorption Ionization coupled to Time-of-Flight Mass Spectrometry; NMR: Nuclear Magnetic Resonance spectroscopy; PTR: Proton Transfer Reaction; REIMS: Rapid Evaporative Ionization Mass Spectrometry.

Fig. 5. Common high-throughput analytical techniques taken as gold standards for food quality assessment and safety monitoring.

Table 1. Use of hyperspectral imaging in various foods quality-related applications

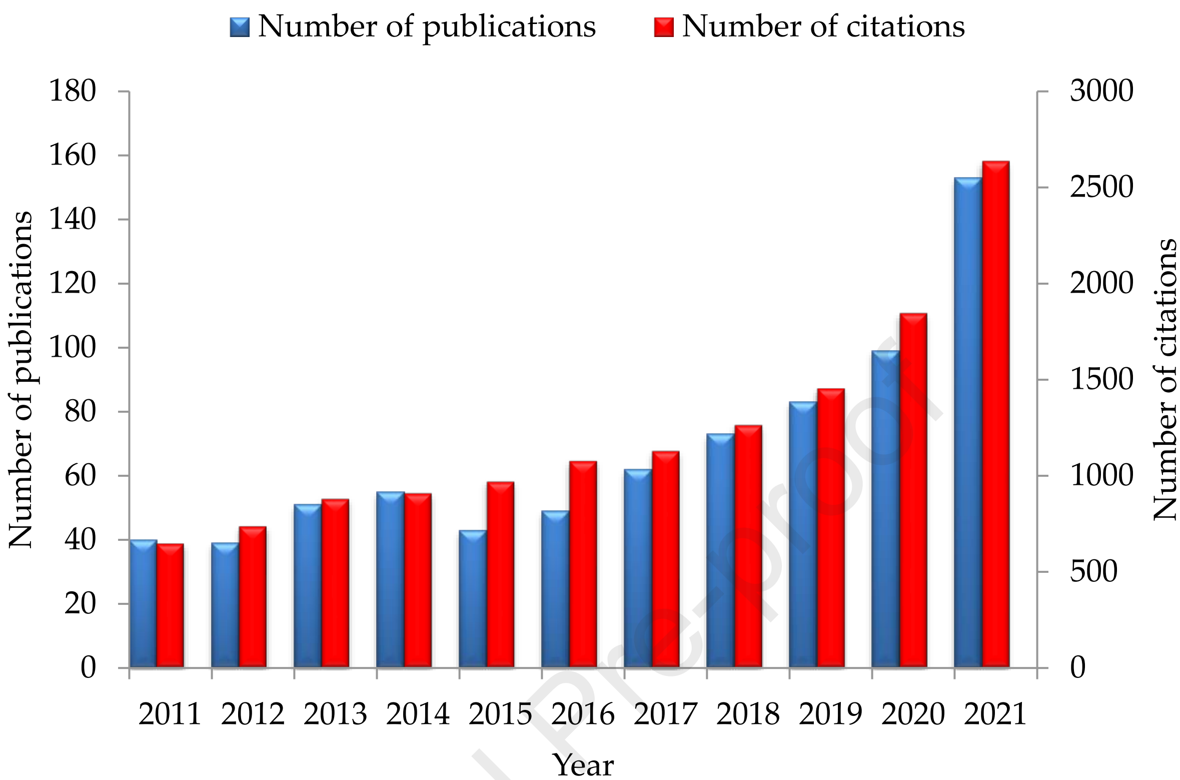
Food	Objective	Spectral Range	Main results	Reference
American bison (*Bison bison*)	Classification of muscles according to ageing period and retail display period, and prediction of color parameters	400-1000 nm	Satisfactory classification results were obtained using PLS-DA model. Redness value (*a* value*) was successfully predicted using PLSR model.	(Chaudhry et al., 2021)
Pacific white shrimp (*Litopenaeusvannamei*)	Prediction of TVB-N	900-1700 nm	After extracting spectral features by deep learning algorithms, LS-SVM model predicted TVB-N with satisfactory accuracy.	(Yu et al., 2019)
	Prediction of TVB-N	860-1700 nm	After building PLSR models with six various pretreatments algorithms, the one built with multiple scattering correction gave the best results. A graphical user interface system was developed to predict the freshness.	(Guo et al., 2021)
Grass carp (*Ctenopharyngodonidella*)	Prediction of TVB-N	308-1105 nm	The best TVB-N prediction result was obtained using PLSR model applied to six optimal wavelengths, selected by a novel algorithm called *Physarum* network combined with genetic algorithm.	(Cheng et al., 2017)
	Detection of fish bones in natural fish fillets	Raman: Excitation; 785 nm line laser (covering a Raman shift range from 820 cm^{-1} - 2847 cm^{-1})	Support vector data description classification model was built on optimal band information, selected using a fuzzy-rough set model, yielding a detection performance of 90.5% with a depth of up to 2.5 mm.	(Song et al., 2020)
Pork	Prediction of TVB-N	842–2532 nm	The PLSR model optimized using random frog (wavelength selection method) and maximum normalization (preprocessing method) showed the best prediction results.	(Baek et al., 2021)
	Prediction of several freshness parameters in frozen pork	Fluorescence: Excitation at 365 nm and emission at 400-1000 nm Vis/NIR: 400–1000 nm	The PLSR model established on the fluorescence data showed good performances in predicting freshness attributes (TVB-N, pH, and color parameters) in frozen samples without thawing.	(Zhuang et al., 2022)

	Prediction of microbial growth	400–1000 nm	A high correlation coefficient between the growth models of *Pseudomonas fluorescens* established using HSI and the plate count method.	(Zhou et al., 2022)
	Detection of offal adulteration in ground pork	400–1000 nm	Good prediction performances were achieved using PLSR models established on eleven featured wavelengths. Limit of detection less than 10 % was obtained.	(Jiang et al., 2021)
Cured pork	Prediction of chemical composition	400-1000 nm	The PLSR model based on nine wavelengths enabled good prediction performances of moisture, protein, and fat contents with R^2 values of respectively 0.8294, 0.8909, and 8241.	(Ma, Sun, Nicolai, et al., 2019)
Atlantic salmon (*Salmo salar*)	Prediction of TBARS and pH	900-1700 nm	Feature wavelengths were selected for developing multispectral imaging system. A satisfactory performance of TBARS prediction model was obtained, enabling a rapid assessment of oxidative degradation.	(Xu et al., 2016)
	Prediction of tenderness	400-1720 nm	Warner–Bratzler shear was predicted with good accuracy by LS-SVM models established on four wavelengths, selected using successful projections algorithm.	(He et al., 2014)
Traditional dry-cured pork belly	Prediction of TBARS as a lipid oxidation indicator	400-1000 nm	Acceptable prediction results of TBARS were obtained using PLSR models established following first and second derivatives pretreatments.	(Aheto et al., 2020)
Crucian carp	Prediction of TVB-N and TPA	900-1700 nm	The PLSR models built on spectral data and textural features, extracted from fish eyes and gills to predict TVB-N and TPA, respectively, show high accuracy.	(Wang et al., 2019)
	Detection of micro plastics in the intestinal tracts	900-1700 nm	SVM classification model was developed, showing promising efficiency and satisfying detection accuracy on three marine fish species.	(Zhang et al., 2019)
Beef, lamb and venison samples including different muscle type	Prediction of intramuscular fat and pH	548 - 1701 nm	PLSR and deep convolutional neural networks models showed good prediction performances.	(Dixit et al., 2021)
Tilapia	Prediction of 4 freshness parameters;	325-1098 nm	A new neural network algorithm (called radial basis function neural networks) was developed	(Shi et al., 2019)

	TVB-N, total aerobic count, *K value*, and sensory evaluation		using nine wavelengths selected by the successive projection algorithm, and the optimized model provided accurate prediction of the 4 freshness indicators.	
Fish cakes	Prediction of core temperature	760-1040 nm	A good prediction model was established giving a root mean square error of prediction of 2.3 °C, even down to 11–13 mm depth.	(Wold, 2016)
Japanese Big Sausages	Determination of pH of cooked sausages after different storage conditions	380 -1000 nm	The PLSR model built on the optimal wavelengths showed good prediction precision (R^2 0.909 and the root mean square error of prediction 0.035).	(Feng et al., 2018)
Potato slices	Prediction of foodborne pathogens (*Escherichia coli*) on the surface of fresh-cut products	400-1000 nm	*E. coli* was predicted with back-propagation neural network model giving a good accuracy (R^2 = 0.976).	(Li et al., 2021)
Plant-based meat analogues	Prediction of proximate composition and alpha-galactosides content	950−1654 nm	A robust prediction of the chemical composition was achieved using PLSR models, and pixel-by-pixel prediction allowed the tracking of components distribution.	(Squeo et al., 2022)
Kyoho grape (*Vitis labruscana cv. Kyoho*)	Prediction of firmness and pH	400-1000 nm	Deep features, extracted via a deep learning approach (called Stacked auto-encoders), were used to build a LS-SVM, achieving an optimal prediction performance for firmness and satisfactory accuracy for pH.	(Xu et al., 2022)
Banana (*Musa spp., AAA group cv. 'Brazil'*)	Prediction of color parameters and firmness	380-1023 nm	Color parameters (L^*, a^*andb^*) and firmness were predicted with acceptable accuracy using PLSR models. Excellent classification results of ripe and unripe banana were achieved.	(Xie et al., 2018)
Beef	Detection of adulteration of beef with duck meat	380-1012 nm	Good performance of predicted values of adulteration levels using PLRS models was achieved. Adulteration maps in the samples with different adulteration levels were generated, enhancing the visual appearance of adulteration.	(Jiang et al., 2019)
Cod	Characterization of lutefisk and classification of four brands	Fluorescence: Excitation at 365 nm and emission at 430-1000 nm	High performance for the discrimination between samples of four different brands of lutefisk using PLR-DA applied on fluorescence data.	(Hassoun, Heia, et al., 2020a)

Lamb, beef, and pork	Authentication and classification of meat species	548-1701 nm	Spectral and spatial information, integrated into deep convolutional neural network models, provided a stable accuracy on line-scanning and snapshot HSI images.	(Al-Sarayreh et al., 2020)
Pearl Gentian Grouper	Detection of freshness of fish stored under different conditions	900-1700 nm	Classification accuracies of 100%, 96.43%, and 96.43% were obtained for respectively fresh, refrigerated, and frozen thawed fish. PLSR models used to predict storage time achieved high modeling and prediction accuracy.	(Chen et al., 2021)
Lettuce	Detection of foreign substances	Fluorescence: Excitation at 365 nm and emission at 430-700 nm	Prediction accuracy of 95.87% for worm detection was obtained, with best classification accuracy being achieved using spectral images with a pixel size of 1×1mm.	(Mo et al., 2017)
Cod (*Gadus morhua L.*)	Monitoring thermal treatments and storage time	Fluorescence: Excitation at 365 nm and emission at 430-1000 nm	Fluorescence intensity was decreased with increasing cooking temperature and storage time. Classification accuracy of 92.5% was obtained.	(Hassoun et al., 2020)

TVB-N: Total volatile basic nitrogen; HSI: Hyperspectral imaging; PLS-DA: Partial least square discrimination analysis; PLSR: Partial least squares regression; LS-SVM: Least-squares support vector machine; TPA: Texture profile analysis; TBARS: Thiobarbituric acid reactive substance; Vis/NIR: Visible/Near infrared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Number of publications
Number of citations
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
Year

Fig. 1


Autonomous robots
Simulation
Big Data analytics
FOOD
QUALITY 4.0
Horizontal/vertical integration
Augmented reality
Industrial Internet of Things

Fig. 2

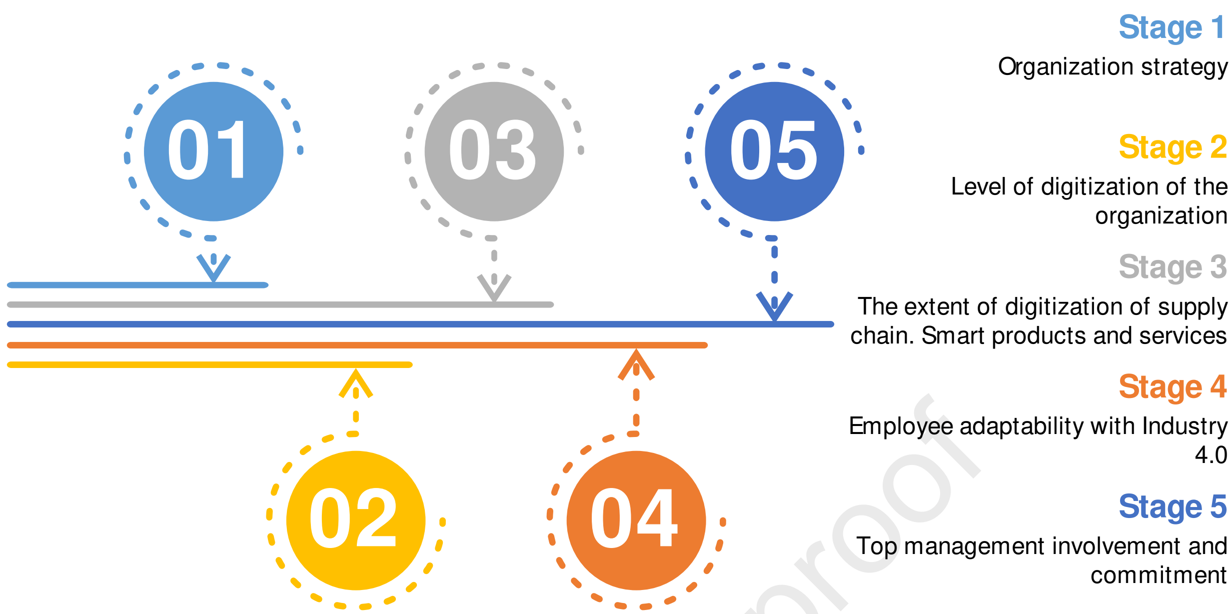
01
03
05
02
04
Stage 1
Organization strategy
Stage 2
Level of digitization of the organization
Stage 3
The extent of digitization of supply chain. Smart products and services
Stage 4
Employee adaptability with Industry 4.0
Stage 5
Top management involvement and commitment

Fig. 3

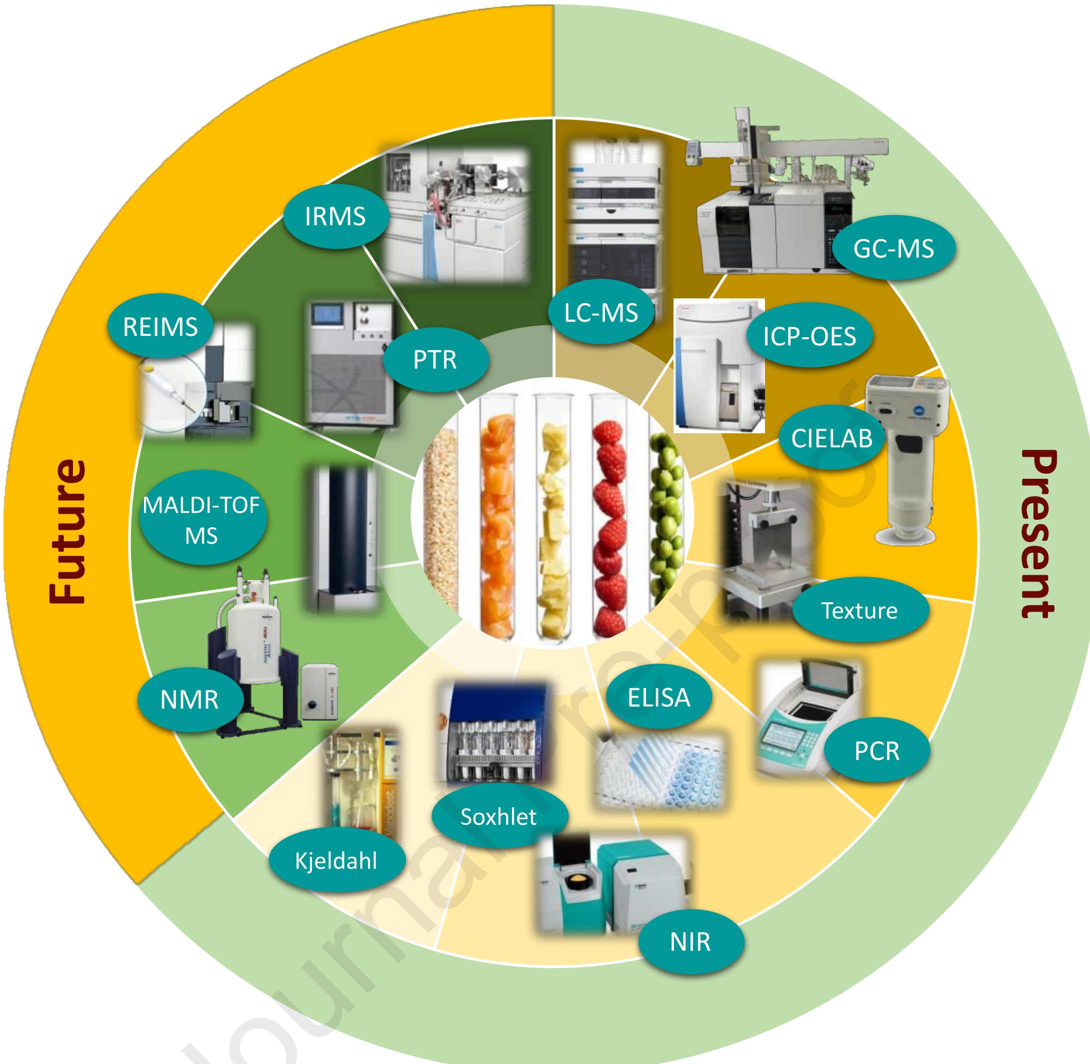
Future
Present
IRMS
REIMS
PTR
MALDI-TOF MS
NMR
LC-MS
GC-MS
ICP-OES
CIELAB
Texture
PCR
ELISA
Soxhlet
Kjeldahl
NIR

Fig. 4


NMR
1H-, 13C-, 37P
Authenticity
Safety
LC-MSMS
TOF, QqTOF, Orbitrap
NIR and FTIR
Traceability
Quality
CE
CE-MS

Fig. 5

HIGHLIGHTS

- Consumer interest in food quality call for advanced and reliable analytical methods
- Industry 4.0 has offered numerous opportunities in many fields, including food analysis.
- Food Quality 4.0 concept - determination of food quality using Industry 4.0 technologies
- AI, Big Data, and smart sensors are important enablers of Food Quality 4.0
- Innovations, digitalization, and automation experienced a massive boost

Declaration of interests

☒ 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.

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Food quality 4.0: From traditional approaches to digitalized automated analysis

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