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The contribution of digital and sensing technologies and big data towards sustainable food supply and value chains

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Modern digital and sensing technologies enable agile and modern food supply and value chains. These technologies contributed to the development of analytical tools to assess food composition, food safety and security (*e.g.* authenticity, contamination, fraud, and provenance). The utilization of digital and sensing technologies determines that a large amount of data is generated during the analysis of food ingredients and products. In this context, big data is defined as the rapid collection of complex data in large quantities during the analysis of foods using sensors (*e.g.* electronic noses and infrared spectroscopy). Therefore, to implement an application, the data must be analysed and interpreted using different data analytics, statistics and machine learning tools. This paper presents the definition of big data, as well as examples of the utilization of digital and sensing technologies combined with data analytics to develop applications targeting food safety and security in the food supply and value chains.

Sustainability spotlight

The UN SDG define improvements in the quality of life of the population in developed, emerging, and developing countries, covering social and economic aspects, with a major focus on environmental sustainability. The incorporation of digital technologies into the agri-food sector has increased the efficiency, productivity, and sustainability of the food systems. Innovations including artificial intelligence (AI), robotics, in-ground and remote sensors, connectivity, and internet of things (IoT) have been also recognized to be critical for the successful implementation of the UN-SDG. This article provides an overview of the contribution of sensing technologies and data analytics, and advantages and challenges of their utilization in the food supply and value chain.

1. Introduction

Recent years have witnessed a wide range of disruptions in the food supply and value chains directly or indirectly associated with pandemics (*e.g.* COVID), regional wars, and climate change.[1–4] Furthermore, technological changes resulting from the utilization of artificial intelligence (AI), internet of things (IoT), blockchain, machine learning (ML) and sensing technologies have led to disruptions that have influenced not only the food production systems but also the food supply and value chains (see Fig. 1).[5–7]

Consumers and the food manufacturing industry demand accurate and comprehensive analytical systems and quality control (QC) tools to assure and monitor the chemical composition, safety, and provenance, of both food ingredients and food products. This has become even more important due to the increase in the number of cases associated with intentional or unintentional adulteration and fraud in food ingredients and food products such as dairy products,[8–10] seafood,[11,12] meat and meat products.[13–16]

This paper presents the definition of big data, as well as examples of the utilization of digital and sensing technologies combined with data analytics to develop applications targeting food composition, safety and security in the food supply and value chains.

2. Digital and sensing technologies and big data

2.1. Digital and sensing technologies

Digital and sensing technologies (*e.g.* biosensors, electronic noses, and infrared spectroscopy sensors) have been included to analyse and monitor the composition, authenticity, and functional properties of agricultural commodities and food ingredients at the production site (*e.g.* farm), and along the entire supply and value chains.[17–19] A range of technologies has boosted our analytical ability to measure the composition and other characteristics of food ingredients and products at the collection and distribution points (*e.g.* distribution centres and supermarkets) minimising the possibility of deterioration and damage to the food during transport of the sample to the

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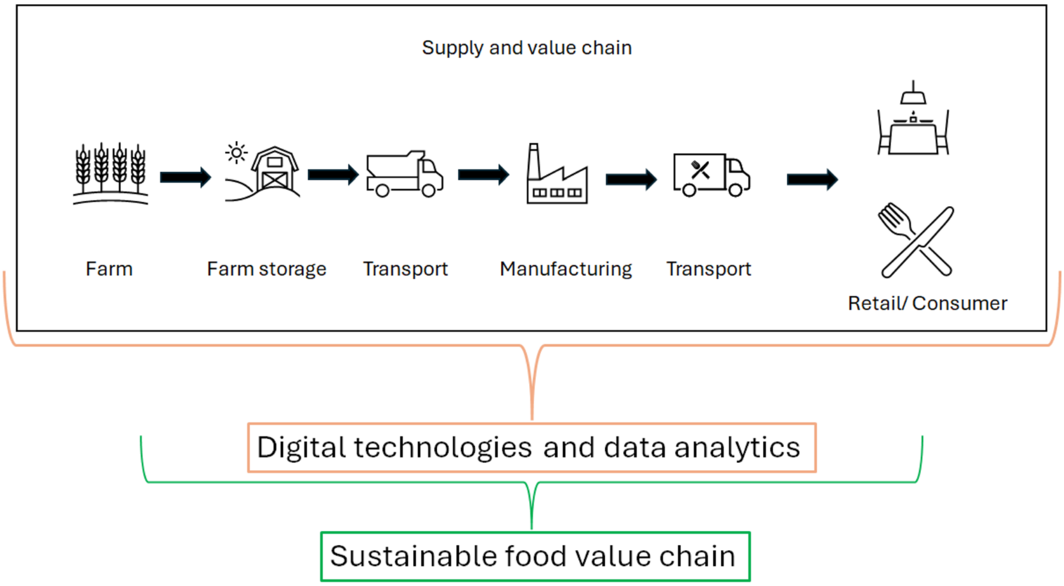

Fig. 1 The role of sensing technologies and data analytics in the sustainability of the food supply and value chain.

traditional analytical laboratory location.[17–19] Therefore, digital and sensing technologies have improved the efficiency of the current analytical and QC methods utilised by the food manufacturing industry to assess and monitor composition, quality and nutritional value of food ingredients and products.[17–19] Furthermore, the occurrence of digital technologies and sensors has provided a wide range of advantages including the elimination or reduction of the need for expensive and time-consuming analytical tools, as well as a reduction in the cost of analysis along the food supply and value chains.

2.2. Big data

The definition of big data is concurrently associated with rapidly collected and complex data in huge quantities.[20–22] Big data is linked with the large amounts of data generated using both digital and sensing technologies (*e.g.* electronic noses, biosensors, optical sensors, drones, *etc.*). Both the amount and complexity of the data collected by the different types of sensors and technologies, is represented and established by the amount of data collected, as well as with the speed at which the information is processed and interpreted.[20–22] The generation of big data has determined that different tools, including the implementation of a wide range of data analytics tools as well as the development of different algorithms have been incorporated in the analysis of foods.[20–22]

3. Sensing technologies and sensors

Recent advances in chemistry (*e.g.* analytical chemistry), physics, electronics and computing science (*e.g.* hardware and software) have led to an increase in the availability and types of sensors in food analysis. These sensors include biosensors, electrochemical sensors, nanosensors, and optical sensors.[17–19,23,24] A sensor is defined as an analytical device that combines a wide range of recognition components (*e.g.* antibodies, nucleic acids, enzymes, whole cells and aptamers) connected with a physicochemical transducer. The different components and characteristics of the sensor combined with a detector allow us to identify (*e.g.* what is it?) and quantify (*e.g.* how much is it? = concentration) a single or several analytes, molecules or compounds existing in a food sample.[17–19,23,24]

One of the main advantages of the utilization of sensing technologies is that they can analyse and identify both biological and chemical analytes or compounds present in any type of food.[17–19,23,24] In addition, the possibility of miniaturization and/or portability of some of the sensing technologies provided additional benefits. This has allowed for the use of small sample sizes or volumes during the analysis of the food sample.[17–19,23,24] Different types of sensors exist, and some of them briefly introduced and discussed in the following sections.

3.1. Biosensors

Developments in nanomaterials, such as nanoparticles and nanofibers have also provided new alternatives for the miniaturization in sensors such as biosensors.[25–29] The inclusion of nanomaterials has improved the analytical ability of electrochemical biosensors by filtering the response of the electrode by increasing the surface area.[25–29] The ability of this type of sensors of providing with a better surface area to volume ratio, give with a greater catalytic and analytics ability, warrant the biocompatibility with the molecule to be analysed, resulting in a lower mass transfer resistance.[25–29] This characteristic has improved the selectivity, sensitivity, time efficiency and cost effectiveness of most of the current biosensors available in the market which are utilised to detect contaminants in foods as it provides conductivity and sensitivity, promotes greater interaction capacity, and lowers detection limits.[25–29] Microfluidics have been incorporated into biosensors with some analytical advantages.[25–29] For example, microfluidics has led to a reduction in both sample and reagent volume (*e.g.* nanolitre), enhancing the sensitivity, and prompted the development of a single platform for both sample preparation and detection.[25–29] However, the main advantage of using microfluidics is in their portability allowing for the development of reusable or disposable and real-time recognition devices. This has allowed for the instantaneous analysis of the analyte (*e.g.* toxins, molecules, and compounds) in a single device with high accuracy.[25–29]

3.2. Electronic noses and tongues

In addition to biosensors, electronic noses (E_nose) and electronic tongues (E_tongue), have been also used to assess food safety as well as to measure or monitor volatile compounds in food ingredients and products.[30–33] An E_nose instrument has been described as a device that simulates the perception of the mammalian olfactory system.[30–33] The main principle of an E_nose instrument is associated with the recognition of odours (*e.g.* volatile compounds) where an E_nose device offers the ability to detect different volatiles or gases with no odour activity.[30–33] The E_nose can be improved to assess or monitor specific molecules or compounds of importance to humans and animals such as the scent of other animals, food ingredients, or spoilage.[30–33] A typical E_nose instrument consists of a series of sensors where metal oxide sensors (MOX), mass spectrometry (MS), ion mobility spectrometry (IMS), gas chromatography (GC), and conducting organic polymers (COP) are the most utilised in food applications.[30–33] However, these types of sensors are well known to lack both sensitivity (ppm or ppb concentration) and selectivity and regrettably, this type of devices cannot respond in a manner comparable with that of the human olfactory system.[30–33] The utilization of E_nose instruments has been extensively evaluated in different food applications such as in quality assurance in bakery products,[34] investigating the quality and composition of alcoholic beverages,[35] and the quality control of edible oils.[36]

Similar to an E_nose, the E_tongue instrument is usually an array composed of various electrodes.[37,38] These electrodes collect the response data obtained from the interaction between the sample and the instrument.[37,38] Different sensor types have been described in the literature where potentiometric, voltametric and impedance sensors are the most commonly utilised in food applications.[37,38] The utilization of E_tongue instruments or sensors is mainly associated with the analysis of liquid samples or a liquid matrix.[37,38]

3.3. Vibrational spectroscopy

Most of the optical instruments and sensors are based on the utilization of light. Vibrational spectroscopy and the techniques associated with it such as near (NIR) and mid (MIR) infrared spectroscopy, Raman spectroscopy, as well as hyperspectral and multispectral imaging methods have been extensively reported in a wide range of food applications.[24,39–44] Vibrational spectroscopy techniques allowed the measurement of molecular structures and chemical bonds as well as the identification of specific molecular species in a food sample.[39]

These techniques capture the vibrational states of a given molecule, providing insights into the chemical, functional, and physical properties of a food sample.[39] Overall, these techniques have several advantages over other analytical methods as they are rapid, require minimal sample pre-processing and preparation, and are relatively cheap and easy to use. Recently, developments in hand-held, portable and miniature instrumentation have also provided new alternatives to assess and monitor issues associated with food safety and security.[40,41] Furthermore, developments in hyperspectral imaging hardware and software have also led to new applications in the analysis of foods along the supply and value chain.[45–47]

4. Data analytics

The increasing amount of data generated by the practical applications and implementation of digital and sensing technologies in food safety and security (*e.g.* authenticity and fraud) requires the utilization of data mining, statistics, chemometrics and ML techniques.[47–50] The assessment of authenticity of food ingredients and products is based on the utilization of data (*e.g.* absorbance at specific wavelengths, concentration of nutrients, pH, *etc*) as the input where classification (*e.g.* classes or patterns) or regression models (*e.g.* prediction of concentration) are used to generate different types of outputs.[47–50] For example, clusters, groups, patterns or even the concentration of specific compounds (*e.g.* chemical composition, nutritional value, origin or provenance) can be estimated or predicted from new input data. The accuracy of the model is dependent on the quality of the input variables (*e.g.* wavelength range, signal to noise ratio, and sample presentation to the instrument) that are used during the development of a model.[47–50] In the application of these techniques, two type of approaches or methods are defined, untargeted and targeted analysis.[47–50] Targeted methods are based on the measurement of known characteristics or properties in the food, or by targeting known ingredients or adulterants, while untargeted analysis is based on the interpretation of the signals collected from the different instrumental methods or techniques used.[47]

A wide range of algorithms exist, providing the means to analyse different types of data in a wide range of food ingredients and food products.[47–50] Examples of these algorithms include Principal Component Analysis (PCA), Partial Least Squares regression (PLS), Support Vector Machine (SVM) classification or regression, Artificial Neural Networks (ANNs), K-Nearest Neighbours (KNNs) and Convolutional Neural Networks (CNNs).[47–50] Recent application in the field of food fingerprinting has reported the utilization of so-called data fusion methods.[47–50] These methods have shown the ability to analyse and combine data obtained from several instruments or techniques.[47–50]

The implementation and combination of sensing technologies with data analytics require in most cases, some level of pre-processing (*e.g.* baseline transformation and derivatives).[51–53] This is usually required during the development of either

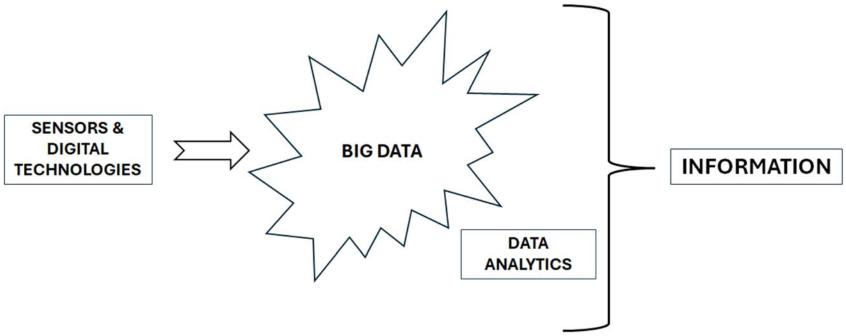

Fig. 2 Sensing technologies, big data and data analytics and the creation of information to be used to evaluate the food supply and value chains.

a calibration or classification model.[51–54] Furthermore, together with the selection of the appropriate algorithms and pre-processing methods, sampling and sample preparation are important factors that should be considered when chemometrics methods are utilised.[55,56] Fig. 2 illustrates how sensing technologies, big data and data analytics contribute to the creation of information that can later be utilised to evaluate or monitor the safety and composition of food ingredients and products along the supply and value chains.

5. Benefits and challenges of big data and sensing technologies in food

The implementation of both digital and sensing technologies has improved the analytical ability of the QC laboratory, reducing the cost of analysis of food ingredients and products from farm to fork. The practical implementation of digital and sensing technologies has led to the collection of large amounts of data where the definition and use of big data have been determined by different users. Nevertheless, the use of big data has created new challenges with development and implementation of sensing technologies in food applications.

One of the main challenges during the application of these tools is the lack of clarity of the objective and/or advantages of the utilization of digital or sensing technologies to analyse food ingredients and products. Sensors are utilised to collect large amounts of data; however, these data are only used to analyse one molecule or compound in a process called calibration. Although this is a valid approach, the advantages of collecting large amount of data (*e.g.* fingerprint of the sample or process), is not universally explored to learn about the totality of the food system or process. Furthermore, issues associated with the signal collected (*e.g.* absorbance at specific wavelengths), the signal to noise ratio, and drifts in the collected signal during the life of the sensors (*e.g.* biosensors and electronic noses) are not well understood or ignored.[51] Different data analytical approaches or algorithms have been also evaluated for the development of classification models (*e.g.* discriminant and cluster analysis) or to build a regression model (*e.g.* calibration models) to predict the concentration of specific compounds in the food sample.

Different research reports and commercial applications concluded that the use of sensing technologies allows for the development of efficient and robust systems to assess and monitor issues associated with food composition and safety in a wide range of fresh products and food ingredients. The utilization of sensing devices is providing the food industry with a robust analytical tool that can be incorporated into decision management systems or tools.[57–60] The development of these type of systems will provide better options to monitor food chemical composition and properties of different types of foods[60] as well as to assure the safety (*e.g.* microbial contamination) of food ingredients and products.

Despite the advantages that these technologies provide, the implementation of these tools or systems is not fully embraced by the food manufacturing industry.[57–59] Traditional analytical and QC methods such as proximate composition, high performance liquid chromatography (HPLC), GC and MS spectrometry, are still preferred by analysts over the use of sensing technologies. In some cases, the utilization of sensing devices or systems is still considered by both researchers and practitioners in the field of food science as "*black box*" approaches due to many reasons.[41,42,51] This can be attributed to the low cost of the available devices compared with other types of laboratory equipment, in addition to the lack of understanding of the time and effort required to develop the whole application (*e.g.* calibration development, model validation and maintenance). This is often exacerbated by the lack of training, the preference for classical food safety analytical methods over the new technologies, and the lack of understanding of the principles underlying the development and implementation of these tools by the food manufacturing industry.

6. Future directions and conclusions

As stated in the above sections the incorporation and implementation of digital and sensing technologies and data analytics have led to different disruptions in the food supply and value chain. However, the data generated by this type of applications have enabled the development of systems that better evaluate and monitor a wide range of attributes at the different steps during the manufacturing, storage and transport of foods. These data rich tools are providing the information that can be used to better manage as well as understand the full manufacturing process, including the quality of the product and its safety.

Advances in handheld devices, sensor miniaturization, and IoT, among others have determined that these tools move away from the traditional laboratory settings into the production facility, storage shed or even the supermarket. However, risks associated with the excessive use of these techniques are also concomitantly great. The lack of knowledge about the sensor background (*e.g.* hardware and physics), data analytics and pre-processing (*e.g.* algorithms) and the associated issues during the development of the application are hindering the wide utilization of these tools. Furthermore, the lack of training beyond that provided by the company that sells the instrument, or the software is critical. These same issues can be considered to enable the inclusion of other disciplines into the food manufacturing industry, fostering an environment of collaboration with different STEM disciplines (*e.g.* mathematics, physics and data analysis).

Digital and sensing technologies have proven that they provide high value data and information to assess and guarantee the safety of food ingredients and products along the supply and value chain. The recent improvements n instrumentation (*e.g.* miniaturization, portability, and robustness), and the timely training on the utilization and interpretation of the models have the ability to expand trustworthiness, contributing to the standardization of methods and systems along the food supply and value chain. Increasing the amount of data and information available about the food process, beyond quality, will improve the efficiency and sustainability of the system (*e.g.* monitor energy and water usage, monitor changes in temperature during the process, and detect faults or any issues during the manufacturing process) and reduce waste along the supply and value chains. Awareness about the limitations of these techniques, as well as a proper understanding of the data analytics used to data mine the big data generated will avoid doubtful conclusions being made from the application of these techniques.

Data availability

No datasets were generated or analysed during the current study.

Conflicts of interest

There is no conflict of interest regarding the publication of this paper.

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