The fourth industrial revolution in the food industry — Part I: Industry 4.0 technologies

Abdo Hassoun[a,b,*], Abderrahmane Aït-Kaddour[c], Adnan M. Abu-Mahfouz[d,e], Nikheel Bhojraj Rathod[f], Farah Bader[g], Francisco J. Barba[h], Alessandra Biancolillo[i], Janna Cropotova[j], Charis M. Galanakis[k,l], Anet Režek Jambrak[m], José M. Lorenzo[n,o], Ingrid Måge[p], Fatih Ozogul[q], Joe Regenstein[r]

[a] Sustainable AgriFoodtech Innovation & Research (SAFIR), 62000 Arras, France

[b] Syrian Academic Expertise (SAE), 27200 Gaziantep, Turkey

[c] Université Clermont Auvergne, INRAE, VetAgro Sup, UMRF, 15000 Aurillac, France

[d] Council for Scientific and Industrial Research, Pretoria, South Africa

[e] Department of Electrical & Electronic Engineering Science, University of Johannesburg, Johannesburg 2006, South Africa

[f] Department of Post-Harvest Management of Meat, Poultry and Fish, Post-Graduate Institute of Post-Harvest Management, Roha, Raigad, Maharashtra 402 116, India

[g] Saudi Goody Products Marketing Company Ltd. Jeddah, Saudi Arabia

[h] Nutrition and Bromatology Area, Department of Preventive Medicine and Public Health, Food Science, Toxicology and Forensic Medicine, Faculty of Pharmacy, University of Valencia, València, 46100 Spain

[i] Department of Physical and Chemical Sciences, University of L'Aquila, 67100, Coppito, L'Aquila, Italy

[j] Department of Biological Sciences in Ålesund, Norwegian University of Science and Technology, Ålesund, Norway

[k] Research & Innovation Department, Galanakis Laboratories, Chania, Greece

[l] Food Waste Recovery Group, ISEKI Food Association, Vienna, Austria

[m] Faculty of Food Technology and Biotechnology, University of Zagreb, Zagreb, Croatia

[n] Centro Tecnológico de la Carne de Galicia, San Cibrao das Viñas, 32900 Ourense, Spain

[o] Área de Tecnología de los Alimentos, Facultad de Ciencias de Ourense, Universidad de Vigo, 32004 Ourense, Spain

[p] Nofima - Norwegian Institute of Food, Fisheries and Aquaculture Research, Ås, Norway

[q] Department of Seafood Processing Technology, Faculty of Fisheries, Cukurova University, Adana, Turkey

[r] Department of Food Science, Cornell University, Ithaca, New York, 14853-7201, USA

* Corresponding author. E-mail addresses: a.hassoun@saf-ir.com (A. Hassoun).

ABSTRACT

Climate change, the growth in world population, high levels of food waste and food loss, and the risk of new disease or pandemic outbreaks are examples of the many challenges that threaten future food sustainability and the security of the planet and urgently need to be addressed. The fourth industrial revolution, or Industry 4.0, has been gaining momentum since 2015, being a significant driver for sustainable development and a successful catalyst to tackle critical global challenges. This review paper summarizes the most relevant food Industry 4.0 technologies including, among others, digital technologies (e.g., artificial intelligence, big data analytics, Internet of Things, and blockchain) and emerging technologies (e.g., smart sensors, robotics, digital twins, and cyber-physical systems). Moreover, insights into the new food trends (such as 3D printed foods) that have emerged as a result of the Industry 4.0 technological revolution will also be discussed in Part II of this work.

The Industry 4.0 technologies have significantly modified the food industry and led to substantial consequences for the environment, economics, and human health. Despite the importance of each of the technologies mentioned above, ground-breaking sustainable solutions could only emerge by combining many technologies simultaneously. The Food Industry 4.0 era has been characterized by new challenges, opportunities, and trends that have reshaped current strategies and prospects for food production and consumption patterns, paving the way for the move towards Industry 5.0.

KEYWORDS: Autonomous robots; artificial intelligence; big data; blockchain, digital transformation; smart sensors; Internet of Things

1. Introduction

The world faces challenging health, demography, and nutrition crises, which need innovative solutions and sustainable food systems (Galanakis 2020). Indeed, tackling current significant challenges, such as climate change induced by global warming, pollution, biodiversity loss, deforestation for food production, overfishing, food waste, and food loss, the rapid increase in the world population, and the risk of new disease or pandemic outbreaks requires innovative, sustainable, and practical solutions to secure sufficient food for all (Boyacı-Gündüz et al. 2021; Mondejar et al. 2021). One dilemma is that while the food industry is already one of the most significant contributors to climate change, food production needs to be increased to meet the growing food demand of the increasing population. Therefore, many food manufacturing industries have recently been under unprecedented pressure to adopt various sustainable technologies, and innovate and meet high efficiency and performance standards (Chapman et al. 2021; Chakka et al. 2021).

The fourth industrial revolution or Industry 4.0 (or even 4IR as it is abbreviated) has been gaining momentum in agricultural and industrial sectors, including the food industry. Considering the Scopus database, the number of published papers dealing with the Food Industry 4.0 enabling technologies has increased from only 2 publications in 2015 to more than 50 in 2021 (**Figure 1**). A sharp increase in the number of citations has also been observed for the same time period. This may be explained by the increased awareness of the potential of Industry 4.0 technologies and digital solutions to contribute to food systems' environmental sustainability. Additionally, the ongoing COVID-19 crisis has significantly accelerated the adoption of digital technologies throughout the entire food supply chain (Bakalis et al. 2020; Amentae & Gebresenbet 2021). Industry 4.0 embraces advanced physical, digital, and biological technologies (Maynard 2015; Massabni & Da Silva 2019; Chapman et al. 2021). It includes, but is not limited to, artificial intelligence, machine learning, big data, the Cloud, the

Internet of Thing (IoT), blockchain, smart sensors, robotics, cybersecurity, and digital twins and cyber-physical systems (CPS) (Bai et al., 2020; Galanakis et al., 2021; Jagtap et al., 2021; Jambrak et al., 2021; Konur et al., 2021; Liu et al., 2021).

Artificial intelligence (AI), machine learning (ML), and big data are essential components of Industry 4.0 for the food industry and many other production domains. ML is a subset of AI, and it includes algorithms used to find patterns in data to make classifications and predictions (Khalil et al. 2021; Saha & Manickavasagan 2021). The AI revolution has become one of the main drivers of Industry 4.0. This is mainly due to the digitalization of almost everything, giving a massive amount of data, which is characterized by its Variety, Velocity, and Volume (the 3 Vs of big data). Big data has thus become the new norm, allowing AI and ML to advance at an exponential pace. Big data analytics are also closely related to the emerging Industry 4.0 components such as blockchain and IoT (Jin et al., 2020; Liu et al., 2021). The interest in IoT has grown to include a network of devices and other physical objects connected to the Internet through different technologies (e.g., sensors and software) enabling interchange and collection of data. The collected data makes it possible to evaluate the status of a given system and can then be used to optimize the performance of that system (Chapman et al. 2021; Mondejar et al. 2021). Blockchain is another digital technology approach that has emerged under the umbrella of Industry 4.0 and has many applications in various sectors. In the food industry sector, blockchain technology can be used to improve and ensure higher performance of different aspects of food value chain systems, such as those for food safety, food quality, and food traceability (Zhao et al. 2019; Khan, Byun, and Park 2020).

The fourth industrial revolution era has been characterized by highly autonomous intelligent systems in industrial production processes due to the implantation of cutting-edge technologies, such as robotics and smart sensors at all stages of the supply chain. Robotics and autonomous systems have been developing as promising technologies to improve sustainable development and increase the quality, productivity, and efficiency of the food supply chain (Khan et al. 2018; Bader & Rahimifard 2020; Duong et al. 2020; Ren et al. 2022). Smart sensors are increasingly used in the food industry in various production equipment to smartly control, monitor, and optimize multiple manufacturing tasks in real-time, along with improving traceability and food quality (McVey et al. 2021; Ren et al. 2022). For example, optical sensors based on spectroscopy have been increasingly applied to detect changes in the frequency of electromagnetic radiation to monitor food quality, authenticity, or food processing (Hassoun, Måge, et al. 2020; Hassoun, Gudjónsdóttir, et al. 2020; Hassoun et al. 2020; Krause et al. 2021).

Digital twins and CPS have increased in popularity in recent years as important digital elements of Industry 4.0. Digital twining is an innovative simulation technology that incorporates the computer simulation into actual operations. This emerging technology can be used, for example, to extend shelf life and reduce food losses, predict the quality and safety of future food product, and improve the design and control of products and processes (Defraeye et al. 2019; Onwude et al. 2020; Verboven et al. 2020; Defraeye et al. 2021). CPS refers to the integration of computational and physical processes, although many other definitions can be found in the literature depending on the field of application (Lee et al. 2015; Smetana et al. 2021; Dafflon et al. 2021). CPS is considered to be a part of the foundation of Industry 4.0 and it is even considered in some publications as a synonym for Industry 4.0 (Tao et al. 2019; Esmaeilian et al. 2020).

Current review papers about Industry 4.0 in the food industry are limited, although some recent publications have tackled this broad subject at different points in the food system. For example, Jambrak et al. (2021) reviewed some of the Industry 4.0 platforms (such as AI, big data, and smart sensors), with the main focus being placed on non-thermal food processing technologies. A short overview of particular Industry 4.0 technologies in the food industry has also been done by Chapman et al. (2021). Smart digital technologies and IoT were suggested as tools to minimize food losses in the postharvest supply chain for fruits and vegetables (Onwude et al. 2020). In another review paper, blockchain was recently suggested as a promising solution to improve traceability and consumer trust, and to reduce food waste and food loss along the whole food supply chain (Kayikci et al. 2020).

This paper will be focused on reviewing the most relevant Food Industry 4.0 technologies and associated digital transformations. These include AI, ML, and big data analytics, the Cloud, IoT, blockchain, smart sensors and robotics, digital twins and CPS, among others. Although most of the topics discussed in this paper were previously reviewed in more detail, this review is meant to raise awareness of the importance of simultaneously considering a wide range of emerging technologies, which address an important principle of Industry 4.0, namely the convergence between various areas of advanced science, especially physical, biological, and digital disciplines.

2. Historical overview of industrial revolutions

The industrial revolutions are historical periods (**Figure 2**) that have been characterized by the emergence of ground-breaking advances in industrial production, which are mainly related to technological advances. Consequently, lifestyles and daily activities were impacted (Agarwal & Agarwal 2017). The dates for the beginning and the end of each industrial revolution are in debate because of the variety of activities they encompassed and the uneven industrial development in different countries.

The first industrial revolution (18^{th} – early 19^{th} century) was characterized by the first changes towards the intensification of working activities using the invention and upgrade in machinery powered by steam engines. The factories were organized to accommodate more workers and machines, and produce more in a shorter period. During this period, the textile, coal, and iron sectors intensified as well as the chemical sector with the British as the pioneers. The expansion of the first industrial revolution within Europe happened gradually and slowly after the turn of the 19th century when Belgian, French and German industries were gradually developed (Koetsier 2019). The development of gas lighting for public illumination had a significant effect on society during this period (Koetsier 2019). It was also the beginning of the transformation of some food products from household to factory-based manufacturing.

The progression of mechanization, and the intensification and expansion of working activities derived from the first industrial revolution led to the second industrial revolution (19th – early 20th century). During this period, the machine tool industry was consolidated, and the internal combustion engine was developed, which led to fundamental advances in transportation and the birth of the automobile industry (Zhang & Yang, 2020). At the industrial level, the use of conveyors accelerated processes, which increased efficiency and industrial capacity. Innovations in the development and use of new materials (such as alloys, lighter metals, and synthetic plastics) also occurred with those technological advances. In addition, electricity received more attention and replaced steam-powered machines for industrial activities and illumination (Zhang & Yang, 2020). The industry progress was also influenced by political views and decisions of that period, which, for example, led to significant changes in military technology, especially during World War I. After the devastating period of the two world wars, the focus of industrial activity gradually shifted. As a result, an economic boom occurred, which was a turning point for the food industry. Aiming to provide convenient and tasty food products became the new paradigm for food production (Silva et al. 2018).

The third industrial revolution (also known as the digital revolution, from the second half of the 20th century – early 21st century) consisted in a transition from analogue to digital electronic systems. Computers and the internet were significant technological advances, which accelerated communications and facilitated connections around the world. In addition, production became automated using electronic systems. During this period, the development and use of nuclear energy became more important to supply the increasing demand from industrial, public, and household consumers (Xu et al., 2018).

The current and fourth industrial revolution or Industry 4.0 (early 21st century) is marked by high technological developments primarily centered on the internet and full automation, and integrated with digital technologies. This ongoing revolution combines physical, digital, and biological components and allows for the creation of communication and connectivity between all industry stakeholders in real-time (Maynard 2015; Lee et al. 2015; Lu 2017a; Sukhodolov 2019). The automation of mass production is being optimized to include customization and individual customer requests. The main aspects attributed to the development of Industry 4.0 are big data, ML, AI, smart sensors, blockchain, cybersecurity, IoT, robotics, digital twins and CPS, among others (Vaidya et al. 2018; Lennon Olsen & Tomlin 2019; Oláh et al. 2020; Misra et al. 2020; Liu et al. 2021). These advanced digital and other emerging technologies have, on the one hand, allowed increased productivity and operational efficiency in the food industry, but on the other hand, they have led to some disruptions in the food supply chain and negative impacts on environmental sustainability (Oláh et al. 2020; Bai et al. 2020; Galanakis 2021; Galanakis et al. 2021). The most relevant Industry 4.0 technologies from the food industry perspective will be discussed in more detail in the following sections. However, it should be stressed that these Industry 4.0 elements could be referred to differently in the literature, mainly due to their application in various fields. For example, some authors claim that IoT, and information and communication technologies (ICT) are the backbone of the Industry 4.0 in the agricultural fields (Demestichas et al. 2020). Others referred to digitalization including blockchain, IoT, big data, and AI as the main Industry 4.0 enablers in the management of the agro-food supply chain (Amentae & Gebresenbet 2021). Robotics and automation, cybersecurity, the Cloud, 3D printing, simulation, and augmented reality, have been added to the list of the aforementioned digital technologies as being important for the sustainable development of food logistics (Jagtap et al. 2021), while the connectivity, associated with digitalization, robotics, IoT, and cloud computing, have been viewed as the core of Industry 4.0 in intelligent food processing (Khan, Khalid, & Iqbal 2018). Another confusing issue is the diverse definitions, notations, and terminologies in the literature of these emerging technologies; e.g., they may be termed as disruptive technologies (Cozzolino 2019; Galanakis et al. 2021; Galanakis 2021). Thus, no unanimous definition of Industry 4.0 and its enabling technologies has emerged.

3. Fourth industrial revolution technologies

3.1. Big data, ML, AI, and the Cloud

Big data was initially associated with the three V's: Volume, Velocity, and Variety, i.e., unstructured data of different types, generated continuously at high speed, creating volumes that traditional software cannot handle. Later, more V's were added to the definition: Veracity and Value, indicating that truthfulness and usability are even more necessary than size and speed. As a result, big data can address business and societal problems in new and efficient ways, and has already revolutionized many areas such as telecom, transportation, and finance (Bughin et al. 2017) . Even so, in many domains, the hype of big data has shifted towards a focus on data quality, with the realization that the value of data lies in its insights and not in its size (Baldassarre et al. 2018; Reda et al. 2020).

ML is a group of methods and algorithms used to find patterns in data, and make predictions or classifications. In principle, ML covers all processes that use data to fit a model, and therefore range from classical statistical methods such as ordinary least squares regression, through chemometric methods such as partial least squares, to more modern and data-intensive methods such as support vector machines, random forests, K-nearest neighbours, and artificial neural networks (ANN). Deep learning has been important in the ML field. Deep learning consists of multi-layered ANN with strong feature-learning capabilities, making it possible to predict traits from complex data without the need to extract manually features of the data. Most of the successful deep learning applications in the food industry involve image analysis, but recent work also shows that deep learning can eliminate the need for pre-processing spectroscopic data (Zhou et al. 2019; Helin et al. 2021).

AI systems can mimic human intelligence by sensing, comprehending, acting, learning, and explaining (Andersen et al. 2018). Industrial AI is a weak or narrow application AI, which can do clearly defined and specialized tasks. Strong AI, on the other hand, is where the machine more closely resembles human intelligence. The latter is still just a goal for AI development and does not yet exist. Industrial AI is usually based on one or more sensors and external data streams, combined with ML algorithms, and logical or causal constraints. AI converts data and predictions into actions and explanations, yielding solutions such as decision support, abnormality detection, automatic process adjustments, and root cause analysis.

The cloud computing (or the Cloud) and its extensions (e.g., fog and edge computing) are new digital infrastructure systems used to store data on multiple servers. Cloud computing has become an important element of Industry 4.0 due to the increased need for managing the massive amounts of data obtained from the various network platforms (Jagatheesaperumal et al. 2021; Jagtap et al. 2021). Because of their numerous advantages including easy sharing, access to information in real time, and the low cost by having a hosting company responsible for storing and managing the data, yielding benefits from an economy of scale and better total equipment usage. The host company may also provide other services such as cloud-based applications that are becoming popular in many fields (Friha et al. 2021; Jagtap et al. 2021). For instance, cloud computing was used to minimize the carbon footprint of the entire beef supply chain (Singh et al. 2015). However, cloud computing is characterized by its centralized computations and data storage, leading to some challenges such as high latency and inconsistency with various types of new network technologies. Recently, other network computing paradigms, such as fog and edge computing, have emerged to overcome the limitations experienced using cloud computing. Fog computing is based on using local networks (rather than core networks with cloud computing) and enables the computations, communication, and storage to be closer to end users. Edge computing is similar to fog computing and allows data generated by smart devices or sensors to be processed using the device itself or a computer near the device (Zhou et al. 2017; Parikh et al. 2019; Kalyani & Collier 2021). With the rapid development and application of cloud/fog-edge platforms, concerns are increasing with respect to security and privacy issues.

Data types in the food value chain

The majority of data-driven applications in the food chain are focused on instrument-generated data, but solutions that utilize new data streams such as text and transactional data are also being developed (Tao et al. 2020; Sharma et al. 2021). **Figure 3** shows a broad overview of data sources and data-driven solutions along the food value chain. Most of the solutions already implemented utilize local or internal data, i.e., data generated close to the application. Other solutions rely on a combination of data sources of different types across the value chain. Such solutions are still in their infancy due to digital infrastructure, data security, and ownership barriers.

Food domain challenges solved using data and AI

Precision Farming: Huge data sets combined with ML have already been used for decades in breeding and genetics. Even so, modern biotechnologies (such as genomics, transcriptomics, metabolomics, and proteomics) combined with smart sensors for extensive phenotyping of many members of the selected organism enable more efficient and targeted breeding of plants and animals (Nayeri et al. 2019; Niazian & Niedbała 2020). Data-driven solutions can also solve many operational challenges with farming. Examples are yield improvement, deciding optimal harvesting time, efficient feeding/fertilizing, improved health and welfare, and enhanced environmental stewardship (Wolfert et al. 2017; Jinbo et al. 2018; Morota et al. 2018; Finger et al. 2019; Sharma et al. 2020).

Food processing: Food processing resembles chemical and pharmaceutical processing in many ways, and the same technologies are often used across these sectors. Process analytical technology (PAT), advanced process control (APC), model-predictive control (MPC), and statistical process control (SPC) are all concepts aiming at monitoring and controlling important quality attributes to improve efficiency, reduce waste, and ensure product quality. ML and AI have become integral parts of all these control concepts, and successful use-cases have been reported by several branches of the food industry (Tajammal Munir et al. 2015; Kondakci & Zhou 2017; Jerome & Singh 2019; Khadir 2021; Mavani et al. 2021; Macdonald 2021). Apart from optimizing the process and product, a similar methodology can monitor the processing equipment, leading to concepts such as *predictive maintenance* (Dalzochio et al. 2020). This is not a food-specific topic and will therefore not be pursued further here.

Innovation and product development: Continuous new product development is considered to trigger competitiveness in the food industry. Recent studies have shown that AI can reduce R&D costs and increase the success rate for new products. In addition, several studies report that text mining of social media and online communities can be used to automatically identify consumer needs and new product ideas (Kakatkar et al., 2020; Patroni et al., 2020; Zhang et al., 2021). Also, some research has been done on the automatic generation of formulations and process conditions by optimizing predictable quality attributes such as sensory properties, nutrition, and shelf life (Zhang et al. 2019; Trinh et al. 2021). The latter approach benefits from using hybrid modeling, i.e., a combination of ML and mechanical models. The optimization framework can, in principle, take multiple aspects such as sustainability, supply, and government politics into account.

Food safety: Food fraud and authenticity is a challenge where data, ML, and AI can have an important role, both by discovering fraud using analytical data (such as DNA and spectroscopy) and developing early warning systems by monitoring trade flow data and analysing text from media reports (Hassoun et al., 2020; Ulberth, 2020). Likewise, source tracking of foodborne illness outbreaks may be done by combining high-throughput genomic data with text from the internet, such as news articles, social media or review sites, along with geo-spatial and socio-environmental information (Marvin et al. 2017; Sadilek et al. 2018; Deng et al. 2021).

Retail and marketing: Consumers leave digital traces of their attitudes, habits, and experiences at retailers and online, including location data captured by smartphones. Retailers routinely collect and analyse information from, for example, loyalty cards and online grocery data for individual customer profiling, which can predict buying behaviour and which can be used to create personalized deals and offers (Hu 2018; Montgomery et al. 2019). Sales forecasting can aid retailers in stock management (short-term predictions) and business development (long-term predictions). Recent surveys show that ML techniques can improve such predictions by combining company data with data from external sources (Tarallo et al. 2019; Tsoumakas 2019).

3.2. Smart sensors and robotics

To realize the full promise of Industry 4.0 requires doing real-time monitoring and measurements all along the food supply chain. This requires sensors that are able to monitor the supply chain by measuring critical parameters during continuous production. Sensors are everywhere, especially with recent advances with nanobiotechnology, nanosensors, and biosensors. They have been used to develop a variety of applications in many fields such as the environment, and the medical, agricultural, and food industry sectors (Misra et al. 2020; Javaid et al. 2021; Lugani et al. 2021). Innovations in other Industry 4.0 technologies (e.g., big data and digital twins) have enabled digital sensing technologies to grow and flourish, deliver greater levels of intelligence and communication capabilities, and be used along the food value chain, from farm-to-fork (Mayer & Baeumner 2019; Verboven et al. 2020; Haleem et al. 2021). Various optical spectroscopic and non-spectroscopic sensors can be used to monitor and collect multi-source data along the food supply chain. The following section will discuss some relevant examples of different types of sensors.

Spectral fingerprint-based sensors

Smart sensors, including optical sensors based on spectroscopy, have become one of the main features of Industry 4.0. Spectral fingerprinting technologies have evolved from being traditional laboratory instruments to miniaturized and automated sensors used in smart factories as part of food Industry 4.0 (**Figure 4**). Recent advances in Industry 4.0 technologies have resulted in miniaturized spectroscopy devices and sensor platforms that are portable, affordable, and easy-to-use (Kalinowska et al. 2021; McVey et al. 2021). Application of these sensors have increased to include, among others, control of food safety, composition, nutritional quality, and food traceability, and monitoring processing, and process sustainability (i.e., decrease energy loss and food wastes) (**Figure 4**).

One example of the promising application areas of spectroscopy-based sensors is controlling and optimizing the various processing steps with enzymatic protein hydrolysis (**Figure 5**) to obtain high-value products from multiple industrial by-products. However, the high variability of these materials and the characterization of the reaction in real-time remain the most challenging tasks. Several studies have shown the possibility of using smart sensors based on infrared, fluorescence or Raman spectroscopy, to determine the quality of raw materials (such as protein, fat, and ash contents), to optimize processing parameters (including, among others, reaction rate, enzyme concentration, time, and temperature), and to characterize the final products (e.g., amino acid composition, and molecular weight distribution) (Wubshet et al. 2018; Wubshet et al. 2019; Måge et al. 2021). Thus, several quality parameters (such as sensory properties) of protein hydrolysates can be predicted based on the measurements of the raw materials (uncontrollable process variables) and the applied processing parameters (controllable process variables).

Food authenticity and food traceability are examples of the topics that can be addressed using digitalization and smart sensors (Han et al. 2021; Amentae & Gebresenbet 2021; McVey et al. 2021). Spectroscopic sensors can provide an actual fingerprint of food products that can be used to authenticate food materials. Different spectroscopic sensors (e.g., fluorescence, infrared, or Raman) in a laboratory or miniaturized configuration, combined with chemometric tools, have been used to authenticate food products (Hassoun et al., 2020; Valand et al., 2020). Qin et al. (2020) used multimode hyperspectral imaging techniques to authenticate fish fillets in terms of freshness (fresh versus frozen-thawed products) and species (i.e., six different fish species including red snapper, vermilion snapper, Malabar snapper, summer flounder, white bass, and tilapia that may be substituted for each other). After testing 24 ML classifiers with different datasets, the authors showed that the reflectance spectroscopy technique in the visible and near-infrared regions has the best performance, allowing the development of a low-cost point spectroscopy device for real-time authentication.

Non-spectroscopic smart sensors

For Industry 4.0, the food industry will require more sensors, multi-sensors, biosensors, and autonomous systems for remote and real-time use to improve productivity and efficiency, and to provide complete monitoring of each food production stage. Beside the aforementioned optical sensors, many electrochemical smart sensors have been developed for food safety and quality (Mayer & Baeumner 2019; Ivanišević et al. 2021). They can be used for process control, inserted on-line during food processing, and, in the case of smart modules, even connected and automatized. On the other hand, smart sensors can also be used at the end of the process to ensure food quality and protect the consumers from food damage/spoilage, as in the case of sensors developed for the food packaging industry (Yousefi et al. 2019; Rodrigues et al. 2021). Such sensors can be incorporated into intelligent "smart" packaging materials in the form of bar codes, films, or labels, etc. to give information about changes in time and temperature (time/temperature sensors and indicators), humidity (humidity sensors), oxygen levels (oxygen sensors), pH (pH sensors), chemical composition (specific chemical sensors), or microbial contamination (microorganism sensors) (Yousefi et al. 2019; Rodrigues et al. 2021; Shao et al. 2021; Cheng et al. 2022).

Recent advances in nanotechnology have led to new applications in many fields of food science and industry. Food sensor technologies have benefited from the opportunities offered by nanotechnology, enabling sensor miniaturisation to use low cost, reliable, and highly sensitive nanocomposite materials (Ivanišević et al. 2021; Shao et al. 2021). Thus, micro-and nano-scale devices are being applied as well-functioning alternatives to traditional biosensors (Inbaraj & Chen 2016; Jafarizadeh-Malmiri et al. 2019; Ali et al. 2021). Seymour et al. (2021) reported an example of their application using nano-electrochemical sensors. They established a multi-purpose electrochemical device for smart agriculture by developing a suitable sensing platform for pesticide and nitrite detection (detection limit of 0.22 ng/mL for clothianidin, 2.14 ng/mL for imidacloprid and 0.2 µM for nitrates). Eventually, the system was interfaced with a smartphone to allowed data inspection and handling. Ge et al. (2022) developed a portable wireless intelligent nano-sensor for detecting terbutaline in meat products. The result obtained using the proposed device was compared with alternative, traditional nanosensing technology and high-performance liquid chromatography (HPLC). Their platform had a layer-by-layer design and was made of bimetallic platinum-palladium nanoparticles, carboxylated graphene, and molybdenum disulfide. As in the sensing devices discussed above, the potentiostat of a smartphone was used as part of the system. The different figures of merit of the device were optimized correctly using ML and artificial neural networks. The smartphone-based device provided (in the linear range: 0.55–14.9 μmol/L) results comparable to those obtained using the sensor based on a computer potentiostat (in the linear range of 0.4–14 μmol/L). Measuring actual samples, the recovering of the proposed nano-sensor was between 91–98.4%, i.e., comparable to the recovering obtained using HPLC (93.4–98.6%).

Emphasis has been on smart sensors based on smartphones, and a significant part of the recent literature related to farm/industry 4.0 is focused on their development (Roda et al. 2016; Kalinowska et al. 2021). A brief search of the Scopus database (done in October 2021) focused on the keywords: *smartphone*, *sensor,* and *food,* showing an increase in such publications. As shown in **Figure 6** (top), since 2019, the number of documents associated with these keywords doubled. As expected, these are (mainly) from engineering, computer science, chemistry, physics/astronomy, and, to a lesser extent, from medicine, biochemistry, material science, chemical engineering, and agro-bio sciences (**Figure 6**). The increasing attention to smartphone-based devices is linked to several factors; among others, the high level of performance achieved by their cameras, their wide-spread availability, and their portability. In addition, these devices are associated with IoT and data analysis, without which the collection of data would have been non-productive. However, from a chemical point of view, it is important that these devices are adequately validated and that their repeatability is accurately estimated, in particular when they are used for the analysis of complex matrices (Kalinowska et al. 2021).

Several biosensors for food/beverage quality control, based on the smartphone, have been proposed. Their aims have been multi-fold and cover different aspects of food quality control. Many of these sensing platforms are focused on pathogen and toxin detection (Inbaraj & Chen 2016; Zhou et al. 2020). A relevant example is the work of Sidhu et al. (2020) who developed a smart device for the real-time determination of *Listeria* in water used for hydroponic irrigation. The authors applied a sensing platform of platinum microelectrodes and a smartphone potentiostat. The sensing platform had high sensitivity (3.4 ± 0.2 kΩ log-CFU^{-1}) and a more than acceptable limit of detection (LOD) (48 ± 12 CFU mL^{-1}, in the range 102-104 CFU mL^{-1}), in agreement with the literature. Caratelli et al. (2021) showed the suitability of a paper-based sensor for detecting botulinum neurotoxins (BoNT). Briefly, the proposed sensor used a paper electrode covered with methylene blue connected to smartphone potentiostat. The neurotoxins reacted with the methylene blue causing its depletion to produce a signal that was correlated with the concentration of the BoNT. It could detect both BoNT (A and C) with a LOD of 10 pM. Similar sensors were developed to detect other bacteria, e.g., *Salmonella*, *Escherichia coli*, *Staphylococcus*, and other bacteria species, as well as fungi and/or their metabolites in food (Sergeyeva et al. 2020; Kim et al. 2021; Xue et al. 2021). Besides bacteria and toxins, several smart sensing devices have been developed to detect unwanted substances, e.g., drugs and pesticides in food matrices, with good analytical performance (Kalyani, Goel, & Jaiswal 2021; Majdinasab, Daneshi, & Louis Marty 2021).

Coupling sensors to radio frequency identification tags (RFID) provides opportunities for real time monitoring of food quality, tracking, control, and early warning. RFID are an automatic identification technology of objects, animals, and people that can be obtained using a transponder (Bibi et al. 2017; Fathi et al. 2020; Ren et al. 2022). For example, a RFID without a battery coupled with a digital sensor tag was proposed for monitoring ammonia in packaged food (Karuppuswami et al. 2020). The sensitivity of the sensing elements was evaluated using capacitance and resistance changes. The results showed that the direct probing (based on resistance change) was able to detect a minimum of 3 ppm of ammonia at room temperature with a response and time recovery of 30 and 60 min, respectively.

Autonomous robots

Food manufacturers are struggling to meet consumer demands for varied, safe, healthy, and sustainable food. Industrial robots are an important component of Industry 4.0 and could solve some challenges in the food industry such as difficulty of obtaining appropriate labour, and reduction of time and cost of production (Bader & Rahimifard 2020; Duong et al. 2020). However, robot implementation in the food industry is still limited due to the industry's stringent safety and hygiene requirements, and cost of investment, as well as a lack of understanding of the full benefits of this new technology (Iqbal et al. 2017; Jagtap et al. 2021). Moreover, foods are naturally unique and come in various shapes, sizes, and colours, making it harder to automate these processes using robots (Bader & Rahimifard 2018). The most common application of robotics in the food industry is in end processes, such as packaging and palletizing (Iqbal et al. 2017), where the material handled is more uniform.

As implementing robotics and automation in the food industry has many benefits, it is expected to grow significantly as the food industry adapts rapidly to Industry 4.0 principles and technologies (Jagtap et al. 2021). A variety of food industry sectors (e.g., food processing) already benefit from using robots in some parts of the production process. For example, the Norwegian meat industry is becoming highly automated and robotized with several tasks, such as carcass cutting and deboning in abattoirs and meat factories being done using robots and more advanced machines (de Medeiros Esper et al. 2021). The implementation of more automation in primary and secondary meat processing could increase the efficiency and production capacity while reducing manual labour and production costs (Barbut 2020).

3.3. IoT, blockchain, and cybersecurity

IoT and blockchain are both considered as important digital technologies that are driving significant changes in different fields, including the food industry sector. At the same time, the need for preventative methods used to secure digital information and data from potential cybersecurity attacks is constantly increasing.

IoT

IoT refers to transferring data between interconnected computer devices and machinery. Recent IoT progress has led to the proliferation of interconnected devices, promoting an increase in the usage of various IoT smart applications in different fields ranging from medicine and healthcare, e-commerce, and education, to manufacturing and agriculture (Onwude et al. 2020; Khalil et al. 2021). Although different layers for the structure of IoT according to the application areas have been described, most studies mainly try to establish three layers, namely i) the device layer including sensors, RFID, and other physical devices that collect data, ii) the network layer including all types of network communication protocols that are used to transmit data collected by the device layer, and iii) the application layer, including IoT applications and services (Bouzembrak et al. 2019; Yang et al. 2021; Friha et al. 2021). Application of IoT technology increases connectivity and provides better productivity, quality, and profitability along the entire supply chain. The interaction and exchange of data and information occur between humans and machines as well as between machines and machines (Kamble et al. 2018; Friha et al. 2021; Jagtap et al. 2021). Recent advances in IoT technologies have brought a wide range of applications in different fields including, among others, various processes used for agricultural production (Yang et al. 2021), food safety (Bouzembrak et al. 2019), and food processing (Jambrak et al. 2021).

An essential aspect delivered by IoT is real-time traceability, which allows for quick actions when dealing with product recalls (Jagtap et al. 2021). A food fraud IoT-based system, containing various sensors for temperature, oil, humidity, salt, metal, colour, pH, and viscosity was proposed to monitor adulterants in food products (Gupta & Rakesh 2018). The system was effective and simple, so that it can be used by several actors in the food supply chain (e.g. farmers, consumers and regulatory authorities). RFID has been successfully applied in broad areas including traceability and ensuring food quality and safety in the agrifood sector (Bibi et al. 2017). Bouzembrak et al. (2019) reviewed several studies where IoT devices were used in combination with RFID to track and trace food authenticity (e.g., food safety and quality monitoring, shelf life and pesticide residue monitoring, traceability and anti-counterfeiting, etc.). For example, Alfian et al. (2020) proposed a RFID-based traceability system integrated with IoT for the perishable food supply chain to track product movement and monitor the temperature and humidity of food products.

Some concerns and challenges still remain. The biggest being the lack of infrastructure to host the connectivity needed for seamless data gathering and analysis using IoT. Another issue associated with this technology is the high cost of the implementations. Moreover, the security of the networks is also a major concern (Bouzembrak et al. 2019; Jagtap et al. 2021).

Blockchain

Traditional food supply chains lack traceability and trackability of products, resulting in the absence of labelling transparency, slow product innovation cycles, and complications in logistics. Blockchain technology can be a solution to these food supply chain concerns. Blockchain has been suggested as a promising technology, underpinned by Industry 4.0, consisting of digital, decentralized, distributed ledgers maintained by a network of multiple computers that can promoting trust and transparency in the agri-food value chain (Zhao et al. 2019; Kamilaris et al. 2019; Rejeb et al. 2020; Amentae & Gebresenbet 2021).

Blockchain increases traceability throughout the supply chain, connecting and tracking data from producer to consumer, allowing for more accurate and faster recalls, thus eliminating some risk and offering better quality food. Better traceability means the validity of claims such as ‘’sustainable’’, ‘’organic’’, and ‘’halal’’ can be monitored and authenticated (Kayikci et al. 2020; Javaid et al. 2021). This technology was found to be helpful in the reduction of food losses along a global supply chain (Kayikci et al. 2020). In addition, blockchain can be used as an integrated traceability technology to reduce the risk of a pandemic (such as COVID-19) disruption of the food system. For example, blockchain along with other new technologies (e.g., RFID) have proven to be beneficial for food cold-chain continuity during the ongoing coronavirus crisis (Masudin et al. 2021). When looking to access the data gathered in real-time (e.g., from sensors), it works best in a secure environment, which blockchain technology can facilitate. Kamilaris et al. (2019) reviewed the increased use of blockchain in the food supply chain and determined the types of data gathered at each stakeholder stage (**Figure 3)**.

Several studies suggested the application of blockchain in combination with several other emerging technologies. For example, a decentralized information system based on blockchain, IoT, and HACCP (Hazard Analysis and Critical Control Points), was developed for real-time food tracing in a food supply chain (Tian 2017). Recently, a secure monitoring and reporting system based on blockchain and IoT was developed to allow for the management of transaction integrity, immutability, and transparency of perishable products along the supply chain with a focus on transportation without any human intervention (Bhutta & Ahmad 2021). In another study, a supply chain system based on blockchain, IoT, and advanced deep learning was evaluated with different numbers of users to verify the provenance of agricultural products

(Khan, Byun, and Park 2020). The proposed system was found to be suitable to handle a large number of users, enabling them to check the origin and the supply chain of their food.

The implementation of blockchain in the food industry is still low as most of the systems are in the early piloting stages. Costs and shortage of required technical skills, education and training platforms are the main concerns limiting food manufacturers from utilizing blockchain technology. Moreover, some barriers related to regulation, privacy leakage, limited storage capacity, and latency issues still need to be dealt with. Additional challenges include the digital gap between developed and developing countries, and the lack of trust in cryptocurrencies in some countries (Zhao et al. 2019; Kamilaris et al. 2019; Khan et al. 2020; Jagtap et al. 2021).

Cybersecurity

Industry 4.0 increased the influx of data within food manufacturing companies. More data has become increasingly available, as global digital networks open up access to manufacturing processes, which involves higher cybersecurity risks (Maynard 2015; Duong et al. 2020). Every time a new piece of technology is introduced, cybersecurity becomes a concern. Cybersecurity refers to the processes and availability of technologists with the needed skills that protect information and computer technology systems, such as networks and computers. The protection is needed against cyberattacks that may damage software and hardware or involve costly ransomware (Demestichas et al. 2020).

The food industry's infrastructure makes it more prone to cyberattacks, e.g., the number of stakeholders involved along the supply chain (Jagtap et al. 2021) tends to be greater than other industries. Therefore, increasing awareness of cybersecurity at all stages of the supply chain is needed. Recipe leakages, process tampering, and consumer data theft are of the most concern. Such instances may threaten a company's supply chain, reputation, and profits. Other examples include turning off software and hardware, and tampering with supply chain logistics (Duong et al. 2020).

3.4. Digital twins and CPS

The concept of digital twin has recently emerged and can be defined as a digital representation of a real-world product, process operation, or physical object that integrates various technological developments, e.g., IoT and AI to synchronize physical activities with the virtual world. Statistical, data-driven, and physics-based models are the main types of digital twins (Tao et al. 2019; Verboven et al. 2020; Defraeye et al. 2021; Burg et al. 2021). Digital twins have the potential to increase knowledge and facilitate decision-making in, for example, agricultural fields (Defraeye et al. 2021; Burg et al. 2021) and food processing factories (Verboven et al. 2020). Digital twins could be used to predict postharvest evolution of food quality and tailor supply chains to maximize shelf life and reduce food losses (Onwude et al. 2020; Defraeye et al. 2021).

Although digital twins have been developed in various industrial sectors (e.g., optimization of the operations and maintenance of vehicles, and aircrafts, etc.), their implementations are still in their infancy in the food industry due to several challenges that still remain (Verboven et al. 2020; Burg et al. 2021). Only a few studies have described the application of digital twins in the food supply chain. For instance, digital fruit twins, based on a mechanistic finite element model and coupled with the real-world environmental conditions were developed to simulate the thermal behaviour of mango fruit throughout the cold chain (Defraeye et al. 2019). The results showed that the digital twins can make the refrigerated food supply chain greener by improving refrigeration processes and logistics as well as reducing food losses.

CPS is an important feature of Industry 4.0 and could be considered as a global network infrastructure that integrates the physical and virtual world. CPS shares some essential concepts with digital twins. The application of CPS with Industry 4.0 has the potential to reach the ultimate goal, i.e., achieving smart factories. The concept of CPS is also closely related to IoT and robotics. CPS of food systems can be foreseen as reaching the highest autonomy levels for self-management and self-control (Lu 2017b; Iqbal et al. 2017; Da Xu et al. 2018; Tao et al. 2019; Jagatheesaperumal et al. 2021; Smetana et al. 2021). Application of the CPS concept in the current food industry and agricultural systems is scarce, but multiple domains could benefit from these technologies (Iqbal et al. 2017).

Various examples of possible applications of CPS from a robotic perspective include intelligent food manufacturing systems. These were reviewed by Khan, Khalid, and Iqbal (2018), while Smetana, Aganovic, and Heinz (2021) provided an overview of the current knowledge about CPS applications in the food industry. The concept of CPS can be applied to build food traceability systems. For example, a CPS-based system inspired by fog computing was created by Chen (2017) for food traceability (tracking and tracing) in the food supply chain. The authors used a case study, along with a software system design and implementation. Challenges associated with CPS include the complexity, multidisciplinary, and heterogeneity of CPS. Lack of technical standards and security models are other challenging issues that should be addressed (Lu 2017b).

4. Advantages and common challenges

Important concepts of Food Industry 4.0 are AI, ML, big data analytics, cloud computing, IoT, blockchain, robotics and smart sensors, digital twins and CPS, although other technologies could be considered in other application domains. Industry 4.0 has highlighted the need for multidisciplinary approaches and connectivity between various domains, not least those related to the physical, biological, and digital fields. This connectivity revolution can basically be understood as being based mostly on data; data acquisition using smart sensors, robots, IoT, and other systems, data processing and mining using cloud computing, and data interpretation using AI and other advanced technologies. Most of these technologies are expected to have an important role in future smart factories and production systems with enhanced digitalization and automation. For example, IoT can be seen as the future of food safety while blockchain could become the future of food traceability.

Industry 4.0 technologies could promote digital transformation and sustainable development along the different stages of the food value chain, saving time and reducing cost. By optimizing and including such advanced digital production technologies, energy-efficient food production and zero waste can be achieved while monitor changes in food production systems leading to sustainable processing and mass customization processes that increase speed and efficiency (Oztemel & Gursev 2020; Jambrak et al. 2021). An example is the use of hyperspectral sensors based on different spectroscopic principles to optimize and monitor at any time and stage multiple processing conditions throughout the course of an enzymatic hydrolysis process for various food by-products (Wubshet et al. 2018; Anderssen & McCarney 2020; Måge et al. 2021). These "green" technologies would reduce food waste, and give opportunities to customize food products and obtain desirable products with specific quality attributes. Consequently, it becomes possible to increase profitability, reduce food wastes, optimize customer needs, and increase consumer satisfaction.

By embracing food traceability and digital solutions, processing from raw material to the final product can be monitored. For example, blockchain can be implemented in the food supply chain as a digital and transparent system to track a product's journey from farm to fork, ensuring traceability and authenticity (Rejeb et al. 2020). Implementing the different elements of Industry 4.0 has the potential to improve supply chain modernization, food quality, and authenticity assessments to ensure food safety (Misra et al. 2020). Moreover, it becomes possible to involve consumers in the decision cycle and their education to reduce waste generation (zero waste production) and increase re-use and recycling of packaging material.

Digitalization of the food industry by incorporating elements of Industry 4.0, i.e., big data analytics, smart sensors, autonomous robotics, and the other advanced technologies could lead to greater productivity, better process stability, and customizable products. However, little attention has been paid to the sustainability of Industry 4.0 (Kamble et al. 2018). An intensive focus on innovation, digital skills, digital infrastructure, and cooperation will help to ensure sustainability and achieve the United Nations' sustainable development goals leading to the smart factories concept and putting it into practice, even in developing countries (UNIDO 2020). Beside the sustainability issue, several other challenges related to Food Industry 4.0 technologies still need to be addressed. Overall, adoption of new technologies can seem like a daunting task, and the uptake of these technologies is slower in the food industry compared to other sectors. This might be due to a silo mentality (i.e., the mind-set of not wishing to share information with others) that still exists among some food industry actors (Hassoun et al., 2020; Power & Cozzolino, 2020). It seems that most emerging technologies have not yet gone beyond laboratory scale because of the high implementation costs and lack of adaptability to an industrial environment. Moreover, lack of technical and technological skills is another issue that hinders wider acceptance of Industry 4.0 and its new technologies and innovation.

Other barriers may be related to specific technologies. Although successful applications of AI, ML, and big data analytics have been reported both for specific operations and along the food value chain, adoption of these technologies is still limited. Barriers are related to challenges with data (infrastructure, quality, standardization, security, and ownership), uncertainties about deployment, validation, and maintenance, as well as lack of competence and resources (Bahlo et al., 2019; Sharma et al., 2020). Robotics and smart sensors could enable human-machine collaboration, leveraging recent advances in AI and IoT, but need to become integrated with the food facility's current systems, and the necessity for more flexibility, advanced hardware and software, as well as lower costs are still apparent.

Finally, it is important to emphasize the necessity of intensifying innovation and the need for further automation and digitalization throughout the whole food supply chain. While Industry 4.0 has already helped in certain areas, some of its greatest potential remains mostly untapped and lies in its ability of achieving successful digital transformations and ecological transitions. These can only be achieved by holistic multidisciplinary approaches that embrace simultaneously as many Industry 4.0 technologies as possible, and include all relevant actors in the food industry (e.g., academic research institutions, industrial partners, as well as regulatory and other governmental authorities).

5. Future perspectives and conclusions

The food industry, as have other industries, has experienced four industrial revolutions, evolving from being a small-scale, manually-operated and labour intensive, fragmented activity to a large-scale, highly-automated and digitalized global industry. Recently, the era of the fourth industrial revolution (Industry 4.0) has started, characterized by the fusion of a number of modern digital technologies, such as AI, IoT, blockchain, and other emerging technologies including, among others, robotics and smart sensors. Industry 4.0 technologies have offered a broad scope of possibilities for the food industry and led to the emergence of new food trends, which will be discussed further in Part II of this review.

This review paper has tried to be an up-to-date source of information about the most relevant technological advances of Industry 4.0 in the food industry. This literature review shows that, on the one hand, several opportunities have arisen to reach climate goals, cope with environmental, economic, and social pressures exerted on the food supply chain, and achieve food sustainability and climate resilience. The Industry 4.0 technologies discussed in this paper will contribute to the green transition toward more sustainable, intelligent, innovative food production systems, with improved efficiency and productivity.

On the other hand, the adoption of Industry 4.0 elements by the food industry is not without challenges. For example, security and privacy issues when collecting large amounts of data over time, makes them more vulnerable to confidentiality attacks. Setting common standards and legal frameworks, as well as establishing the proper regulatory environment, is important to ensure the protection and consistency of data, especially with cross-border data flows. Most of the emerging technologies are still confined to laboratory-scale experiments and are not commercially available because of the gap between laboratory-scale research and real-time applications. The studies reported showed that research has addressed many of the aforementioned challenges. Continuous research and development, and intensive collaboration between regulators, research institutions, and industry are required to harness the power of Industry 4.0 in the food industry and reap the opportunities offered by its advanced technologies. Enhanced networks and connectivity are expected to contribute to a greater success of modern sustainable agriculture and the food industry. The application of several Industry 4.0 technologies, especially together, could provide important sustainable solutions, achieving valuable outcomes for public health, and environmental and economic development. Finally, the literature review showed that many human aspects have been ignored in Industry 4.0 technologies and their implementation in the food industry. Therefore, it is likely that humans will be central to a possible fifth industrial revolution (Industry 5.0). Hopefully soon.

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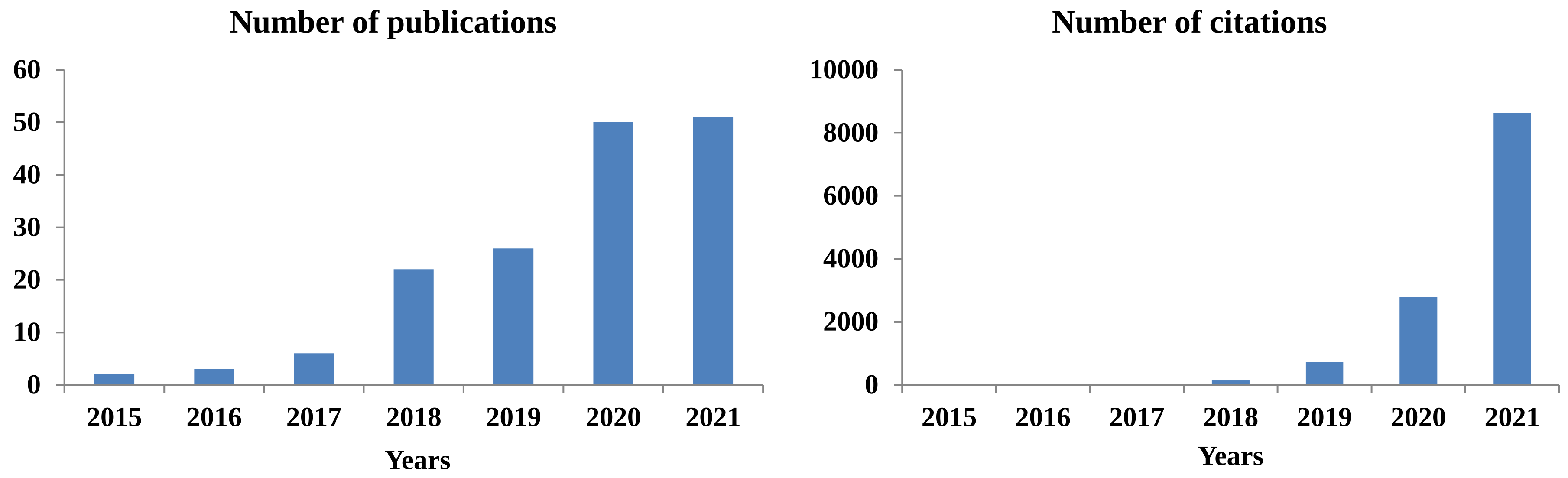


Figure 1. Publications and citations numbers related to the fourth industrial revolution in the food industry. (Search criteria: Article title, Abstract, Keywords: Fourth industrial revolution, OR Industry 4.0, AND Food industry, AND artificial intelligence, OR big data, OR Internet of Things, OR blockchain, OR robotics, OR smart sensors, OR digital twins, OR cyber-physical systems). The data were obtained from Scopus in December 2021.

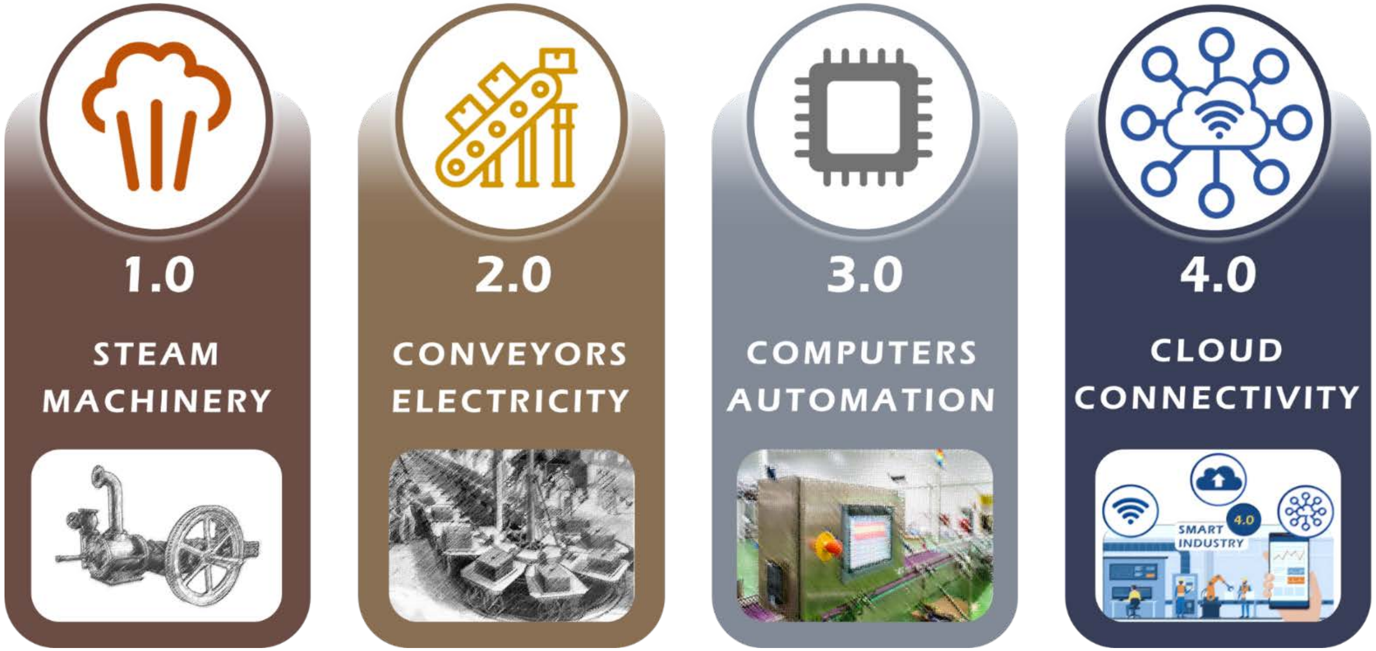
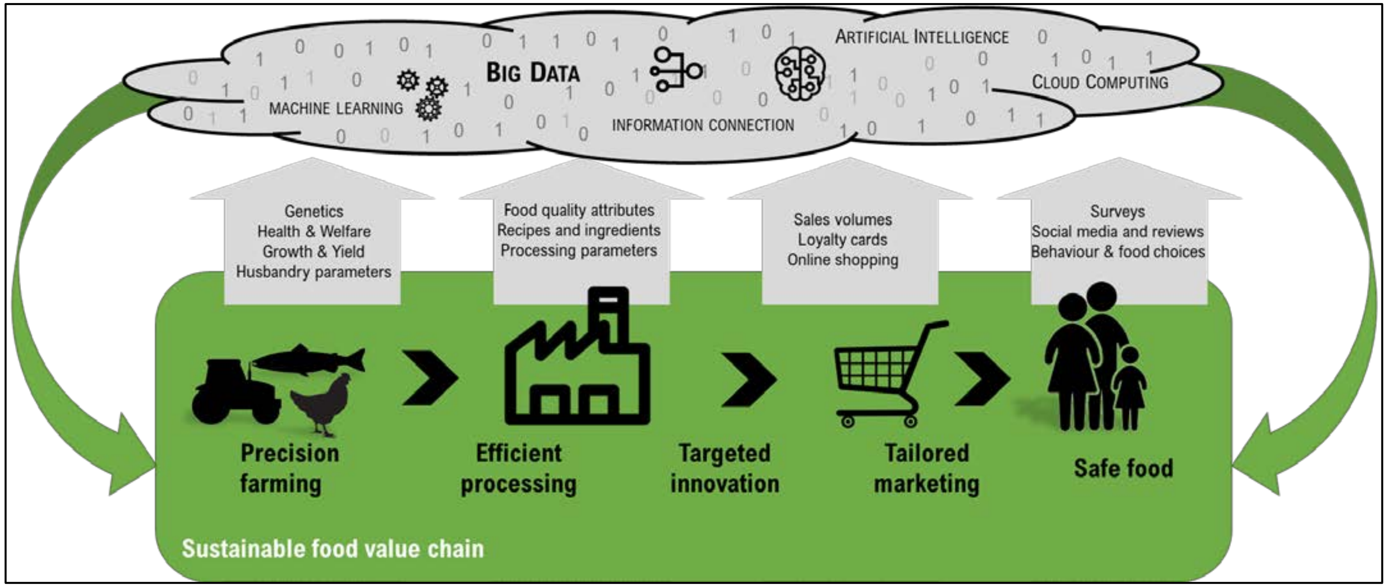
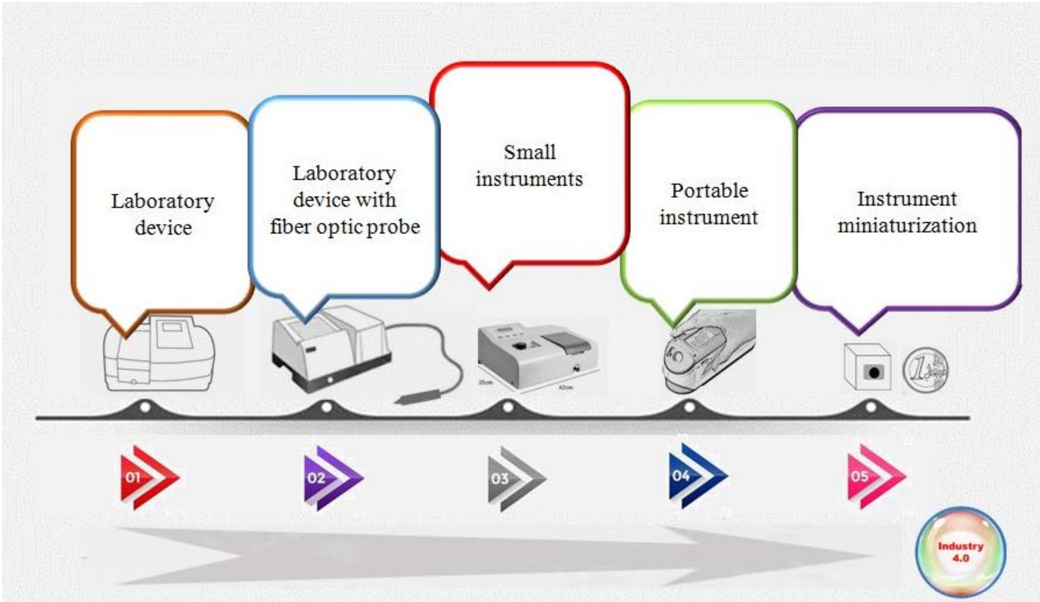


Figure 2. Schematic representation of past and current industrial revolutions

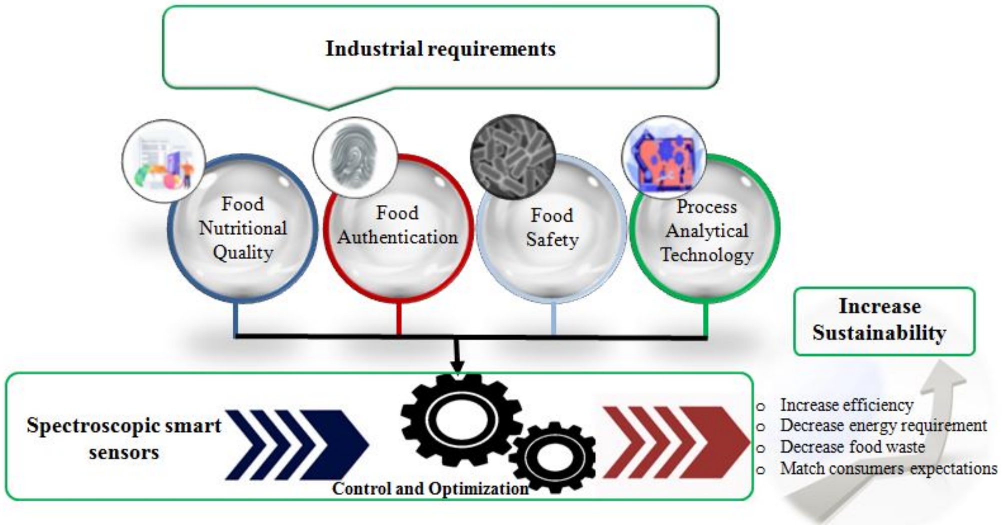


Provider	Producer	Processor	Distributor	Retailer	Consumer
					
Crops, pesticides, fertilizers, machinery and transactions between farmers and producers	Farm, farming practices, crop cultivation process, weather conditions and animals present	Factory, equipment, processing methods, batch numbers, transactions with producers and distributors	Shipping details, storage conditions, transit time, transport method, transactions between distributors and retailers	Food item details, current quality and quantity, expiration dates, storage conditions and shelf time	Information gathered is displayed to consumer through web application

Figure 3. Overview of data sources and information flow along the food value chain (Adapted from Kamilaris et al. (2019)



Laboratory device
Laboratory device with fiber optic probe
Small instruments
Portable instrument
Instrument miniaturization
01
02
03
04
05
Industry 4.0



Industrial requirements
Food Nutritional Quality
Food Authentication
Food Safety
Process Analytical Technology
Spectroscopic smart sensors
Control and Optimization
Increase Sustainability
Increase efficiency
Decrease energy requirement
Decrease food waste
Match consumers expectations

Figure 4. Time line development of smart spectroscopic sensors and their application areas

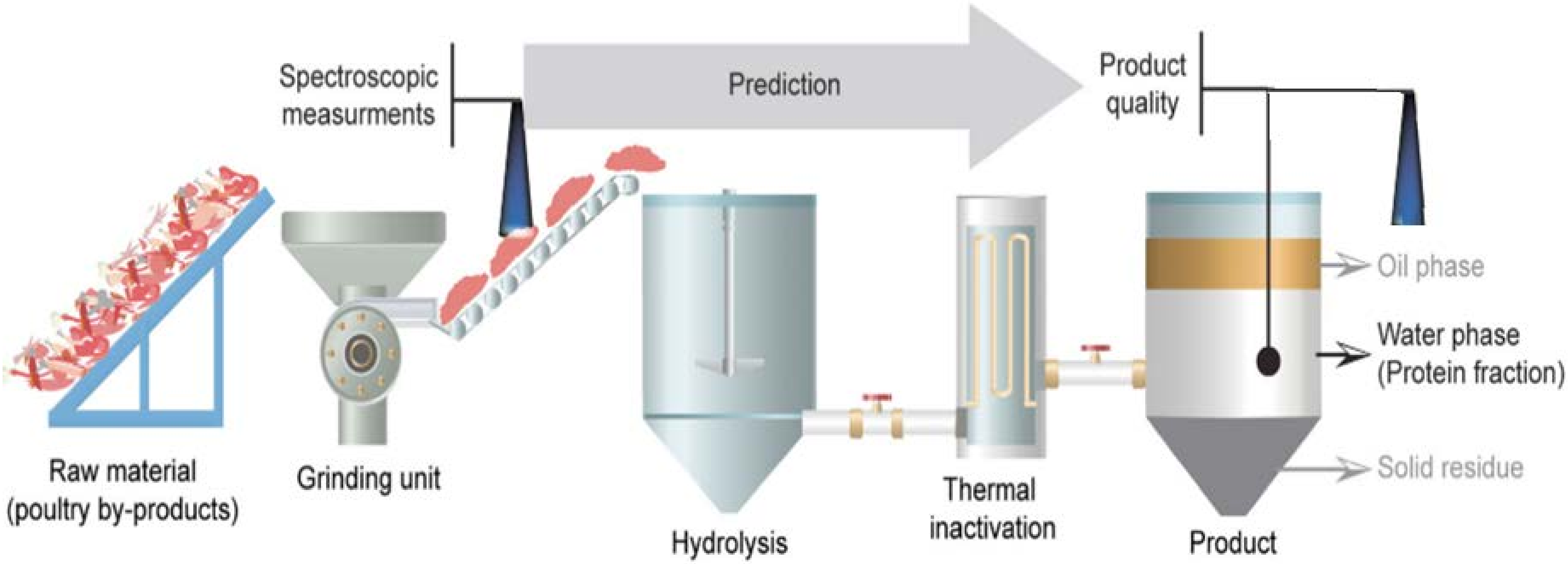
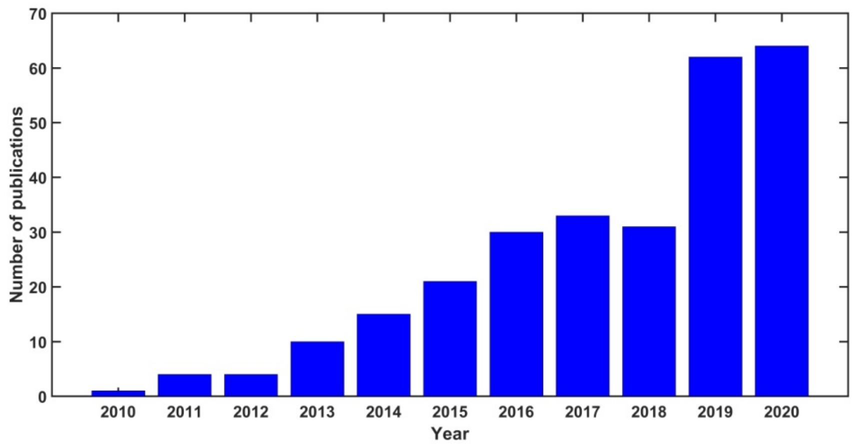


Figure 5. Application of spectroscopic techniques for monitoring the main steps of enzymatic protein hydrolysis (Reprinted by permission from Springer Nature, (Wubshet et al., 2018) (Copyright: 2018) and Elsevier, (Wubshet et al., 2019)).


70
60
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10
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Number of publications
2010
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Year

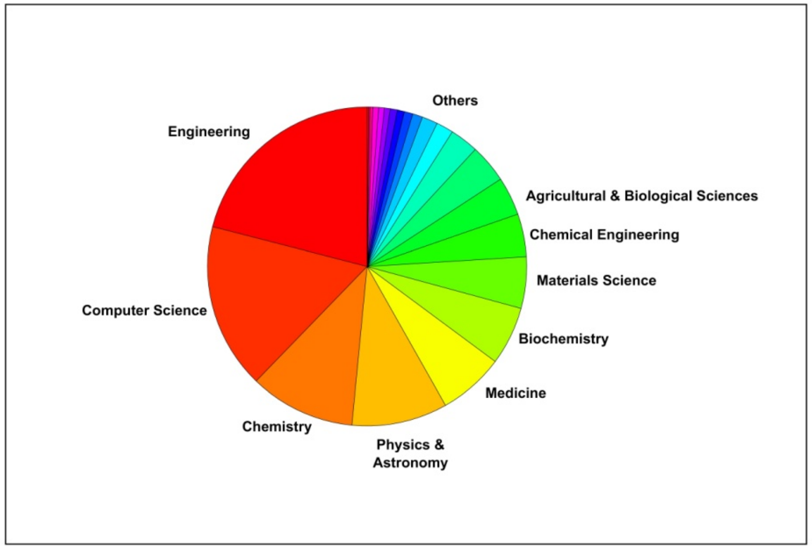
Others
Engineering
Agricultural & Biological Sciences
Chemical Engineering
Materials Science
Computer Science
Biochemistry
Medicine
Chemistry
Physics &
Astronomy

Figure 6. Outcome of a Scopus search of the keywords: “smartphone”, “sensor” and “food”. Top: Number of published documents in the period 2010-2020. Bottom: Pie chart of the application fields.