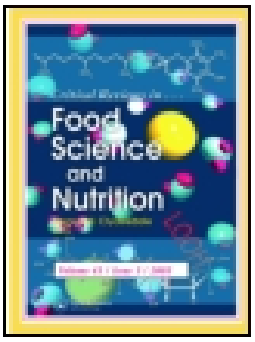

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REVIEW

Smart traceability for food safety

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ABSTRACT
Current food production faces a tremendous challenge due to the growing human population. The global population is estimated to reach 9 billion by 2050 with 70% more food being required. Safe food is an important dimension of food security, and food traceability across the supply chain is a key component of this. However, current food traceability systems are challenged by frequent occurrences of food safety incidents and food recalls that have damaged consumer confidence, caused huge economic loss, and put pressure on food safety agencies. This review focuses on smart food traceability that has the potential to significantly improve food safety in global food supply chains. The basic concepts and critical perspectives for various detection strategies for food safety are summarized, including portable detection devices, smart indicators and sensors integrated on food packages, and data-assisted whole-genome sequencing. In addition, new digital technologies, such as Internet-of-things (IoTs) and cloud computing, are discussed with the aim of providing readers with an overview of the exciting opportunities in smart food traceability systems.

KEYWORDS
Food traceability; food supply chain; sensor and indicator; internet-of-things (IoTs); food safety

Introduction

In 1996, food security was defined at the World Food Summit as the condition that "all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO 1996). Approximately 14% of food products globally are lost during production before they reach the consumers. Part of this loss is attributed to chemical and microbiological contamination in foods (FAO 2019). In addition, food safety has a significant effect on the economy and trade in food because food is increasingly grown for the global market. Unsafe food products also present a constant health risk for consumers in both developing and developed countries. There are a projected 600 million cases of foodborne illnesses accompanied with 420,000 deaths worldwide annually. In the United States, it is estimated that the cost due to illnesses from foodborne pathogens is over $10 billion annually (Hoffmann, Batz, and Morris 2012). Due to the presence of foodborne outbreaks, food recalls precipitated from food safety risks have become a nightmare for the food industry with a business impact of $578 billion annually (Ray et al. 2012). In a rapidly urbanizing world, food consumption patterns are changing to include a higher demand for fresh fruits and vegetables, and minimally processed foods, all of which present a high risk to human health. This demand for these riskier food products creates extra challenges for the food industry to ensure food product safety.

Food supply chain plays an important role in ensuring the safety of food products. Foods are produced on farms, processed in factories, distributed through warehouses, then to retail sales, direct to consumers or to food service establishments. Food contaminants can be introduced at any stage of the food supply chain. For example, pathogenic bacteria (*e.g.*, *Escherichia coli* O157:H7) can be introduced to leafy greens from the contaminated irrigation water (Solomon, Yaron, and Matthews 2002). Another example is melamine incident (one of the most famous food contamination schemes) where melamine were added to a wide range of milk to increase the apparent protein content (Gossner et al. 2009). This food fraud was identified across the entire dairy product supply chain and was difficult to both detect

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and control. Food fraud along with microbial contamination triggered the food industry and governments to improve the safety standards across the food supply chain by implementing improved practices, but the food supply remains vulnerable to food contamination and fraud. Today, food system still lacks traceability and transparency. There is an urgent need to develop efficient technologies to monitor the food supply chain so as to identify and recall unsafe food. As an example of regulatory traceability requirements, the US Food and Drug Administration (FDA) through the implementation of the Food Safety Modernization Act (FSMA) has encouraged the development of improved traceability systems to protect consumers from the contaminated agri-food products. Ideally, such a system will define key processes to facilitate end-to-end traceability throughout the food supply chain.

This review article starts with an introduction of smart food traceability that possesses the capability of reducing the risk of foodborne outbreaks and food recalls. The basic and fundamental properties of the current detection technologies for food safety will then be introduced. Afterward, this review focuses on the discussion of advanced technologies for tackling big data that can complement the current detection technologies for a smart food traceability system.

An era of smart food traceability

Food traceability is a key factor to ensure food safety across the global supply chain in the multi-trillion-dollar food industry. Traceability in the food supply chain is defined as "the ability to trace and follow a food, feed, food-producing animal or substance intended to be, or expected to be incorporated into a food or feed, through all stages of production, processing, and distribution" (Commission 2002). Incorporating more sophisticated traceability into the current food supply chain will lead to a greater assurance of food safety as well as reduce food loss or waste. How food is marketed is changing rapidly as more customers order groceries online for delivery or in-store pick-up. Recent shelter-in-place orders across the world in response to the COVID pandemic of spring 2020 drove this change more rapidly than would have been anticipated a year ago. The introduction of blockchain technology into food logistics is changing how food is marketed and distributed on a global scale. In addition, this technology is driving changes in the structure of global food industry, blurring the lines between manufacturers and retailers, and resulting in a convergence in global food demand and technological advances in how that food is delivered to consumers (Burke 2019). Thus, it is becoming more important than ever to reply on food traceability for the delivery of high-quality foods, particularly perishable foods, to customers' doors.

The ideal smart food traceability system has the ability to track the location of any food, the ingredients it contains, and packaging at any location in the supply chain from producers to consumers. There will be a database about the product in the traceability system. If food recalls are required, a traceability system will help to quickly identify the source of contamination, enabling parties to take effective actions (*e.g.*, removal of contaminated products from the marketplace) and protect consumers from the contaminated food. However, it is still challenging to establish a practical traceability system due to these considerations: (1) every single product contains multiple ingredients that may originate from different sources, suppliers, and even countries; (2) food supply chains are diverse and complicated; (3) advanced and expensive devices (*e.g.*, smart sensors) are required to collect food safety traceable data; and 4) a massive amount of data could be generated from the traceability systems that may be difficult to analyze (Scholten et al. 2016). These data are heterogeneous so that advanced technologies are required to process traceability data and trace food contamination sources or to respond to an incident in a timely manner.

Because current food traceability systems are neither smart enough in terms of type, relevance, and sensitivity for data collection, nor fast and cost-effective enough to address all the aforementioned challenges, the food industry requires smarter technologies specifically digital technology-based food traceability and smart food traceability systems. The core principles of smart food traceability are: (1) to leverage portable sensors and indicators for the collection of more comprehensive, traceable, and timely data about food products, and (2) to develop novel traceability technologies by incorporating emerging digital technologies, such as the internet-of-things (IoTs) and cloud computing. In other words, a smart food traceability system is aimed to improve food safety from farm to fork using advanced detection technologies and digital technologies for analyzing traceability data (Figure 1). On the one hand, the volume and complexity of traceability data will largely expand with the use of sensors and indicators for portable detection, integration on food packages, and whole-genome sequencing (WGS). On the other hand, IoTs and cloud computing, with the aid of wireless technologies, can collect and analyze traceability data in real-time, thereby easing foodborne outbreak investigation.

Current portable detection technologies

The conventional way to determine the safety of food products relies on the detection of food adulterants and contaminants in laboratory settings (Dudeja, Gupta, and Minhas 2016). Although laboratory-based detection can provide reliable and accurate results, sophisticated and expensive instruments are required, which are time-consuming and labor-intensive (Hameed, Xie, and Ying 2018). The limitations of the conventional approaches largely hinder their application for the on-site food analysis, and therefore drive the demand for portable detection technologies that are less expensive and user-friendly. Current portable food detection techniques can be grouped, including portable spectrometers, array sensors, microfluidic lab-on-a-chip (LOC), and smartphone-based analysis.

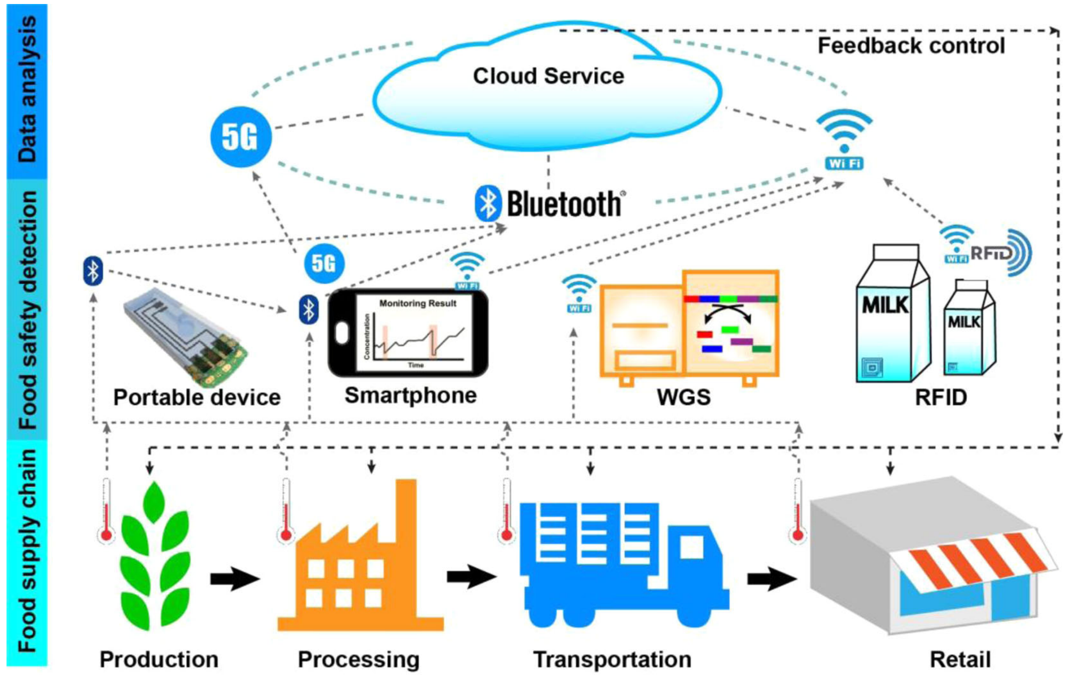

Figure 1. A schematic overview of a smart food traceability system. The core principles of smart food traceability are: 1) to leverage portable sensors and indicators for the collection of more comprehensive, traceable, and timely data about food products, and 2) to develop novel traceability technologies by incorporating emerging digital technologies, such as the internet-of-things (IoTs) and cloud computing.

Portable spectroscopy

Portable spectroscopy enables nondestructive, rapid, and on-site analysis of food compounds and evaluation of food safety, including infrared (IR), Raman, and nuclear magnetic resonance (NMR). Among these portable spectroscopic instruments, IR absorption and Raman scattering spectroscopies measure chemical information of food specimens, while NMR spectroscopy characterizes food materials based on the magnet properties of atomic nuclei (Günther 2013; Hashimoto et al. 2019). One advantage of these portable spectroscopies is their capacity to evaluate food samples in a nondestructive manner through packaging, which can largely reduce the detection cost for food traceability systems. For example, Correia et al. employed a miniaturized IR spectroscopy to evaluate the quality of Arabia coffee through a glass vial (Figure 2a) (Correia et al. 2018). Without physical contact with samples, the instrument can detect adulterants (Robusta coffee and corn) at a low concentration in Arabia coffee. As shown in Figure 2b, Xu et al. utilized a portable single-sided NMR device to detect adulteration of olive oil by sunflower oil and palm oil, and the evaluation was performed in a sealed bottle (Xu et al. 2014). To date, the feasibility of portable spectroscopy in food traceability has been validated, but the measurement may be interfered by the environmental factors (*e.g.*, temperature and moisture) and food compositions.

Array sensors

Array sensors can be used to analyze foods by mimicking human sensory perception systems, such as taste and smell (Patel 2014). When evaluating food sensory properties, the array sensors will generate a pattern of characteristic responses that can be used to identify foods. Various portable array sensors have been developed for food systems, including electronic noses for volatiles or electronic tongues for non-volatiles in liquid (Bandyopadhyay and Sen 2011). For example, a PEN2 portable electronic nose (Airsense Analytics, Germany) fabricated with 10 gas sensors has been demonstrated to detect meat adulteration and confirm the origin of wine, liquor, and edible oil (Tian, Wang, and Cui 2013; Xu, Zhu, and Yu 2017). In this strategy, a signal pattern has been generated when the electronic nose was exposed to volatiles. By deciphering the signal pattern via machine learning and artificial neural networks, food authenticity can be confirmed (Gonzalez-Fernandez et al. 2019; Martinez-Castillo et al. 2019). In another study, Cruz et al. developed an electronic tongue with an array of 6 chemical sensors to assess paralytic shellfish toxins in mussels. The array sensors were immersed in a toxin-containing liquid and produced a pattern of electrical signals, which were recognized through a customized machine learning model to evaluate toxin levels (Cruz et al. 2018). Array sensors have a great potential to be used in food traceability systems for the detection of food authenticity and contamination.

Microfluidic lab-on-a-chip (LOC)

A microfluidic platform integrates miniaturized actuators and sensors in a single system and can be used to perform the detection of food contamination and adulteration (Escarpa 2014). The platform is able to perform complicated food detection procedures in a rapid and automated manner, and requires a small amount of food sample and reagent for each run. For example, Hung et al. fabricated a

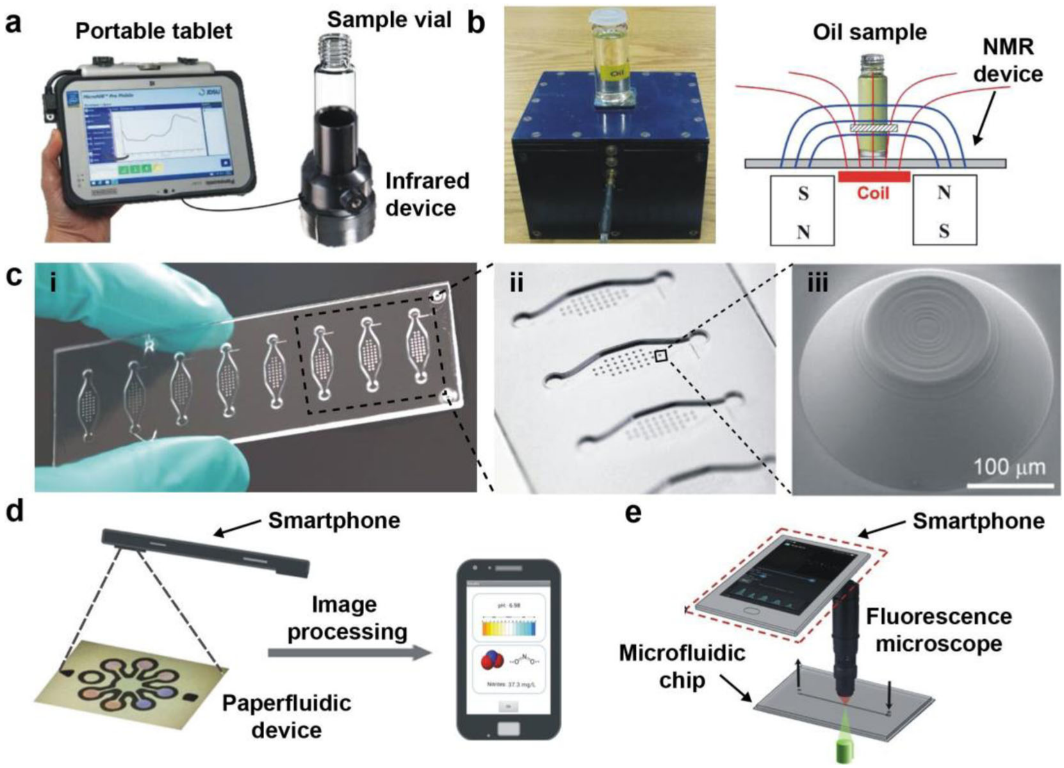

Figure 2. Portable detection devices. (a) a miniaturized infrared spectrometer connected to a tablet (Reproduced with permission from ref. (Correia et al. 2018), copyright 2018, Elsevier). (b) a portable NMR spectrometer for oil quality analysis (left) and its schematic diagram (right) (Reproduced with permission from ref. (Xu et al. 2014), copyright 2014, MDPI). (c) A plastic microfluidic chip: (i) photograph of the microfluidic chip, (ii) microchamber, and (iii) a scanning electron micrograph of the solid phase detection module (Reproduced with permission from ref. (Hung et al. 2017), copyright 2017, Elsevier). (d) a smartphone-based platform for monitoring nitrite (Reproduced with permission from ref. (Lopez-Ruiz et al. 2014), copyright 2014, American Chemical Society). And, (e) a smartphone-based fluorescent microscopic system for detecting *Salmonella* spp. (Reproduced with permission from ref. (Wang et al. 2019), copyright 2019, Elsevier).

microfluidic LOC device using a plastic substrate to detect foodborne pathogens (Figure 2c). The microchip similar to the size of a microscope slide includes solid-phase PCR and supercritical angle fluorescence microlens array (Hung et al. 2017). In addition to the plastics, other materials including silicon, glass, and polymer [*i.e.*, poly(dimethylsiloxane)] have been used to fabricate microfluidic devices, but they have poor practical applications due to relatively high cost. The fabricated devices also require extra instruments to control the fluid flows. In recent years, paper-based substrate has been used to fabricate paperfluidics, which can overcome the limitations of conventional microfluidic devices. Not only is paper an inexpensive matrix, but it also allows automated fluid flow without instrumental assistance via a capillary force that is generated by the micro-sized pores of the paper. For example, Zhang et al. developed a paperfluidics with multiple test zones using chromatographic paper. Using this paperfluidic system, multiple heavy metals and antibiotic residues in foods can be simultaneously detected (Zhang, Zuo, and Ye 2015). Since it is challenging to create a micro-sized channel on a paper-based substrate, paperfluidics can suffer from a lower resolution and sensitivity compared to the conventional microfluidic LOC.

Smartphone-based analysis

Equipped with a digital camera, battery, screen, processor, storage, and wireless data transfer modalities, a smartphone has the functionalities of data collection, processing, interpretation, and sharing, making itself an ideal tool for food analysis. For example, Lopez-Ruiz et al. developed a smartphone-based platform to detect nitrite, a chemical additive in meat products (Figure 2d). The presence of nitrite triggered the generation of a characteristic colorimetric array on a paperfluidic device, and a smartphone then captured its image and performed quantitative analysis via a tailored application (Lopez-Ruiz et al. 2014). In another study, Wang et al. assembled a smartphone-based fluorescence microscopic system for rapid detection of *Salmonella* spp., a leading foodborne pathogen (Figure 2e). The smartphone recorded a video of fluorescence-labelled *Salmonella* moving on a microchip and processed the images using a designed application interface to quantify the number of bacteria (Wang et al. 2019).

Current portable devices are suitable for rapid food inspection and tend to be more miniaturized and cost-effective. However, their on-site applications in the food supply chain may be limited due to data handling. At the remote settings, it is not practical for the current portable devices to process and interpret high-dimensional spectral data or complicated sensing signals. Thus, it will be significantly beneficial for the food traceability system to assemble data transfer and processing to the current portable devices. Once the assembly is achieved, trained personnel are not required to operate devices for food inspection. Most importantly, more reliable data on geographical origin,

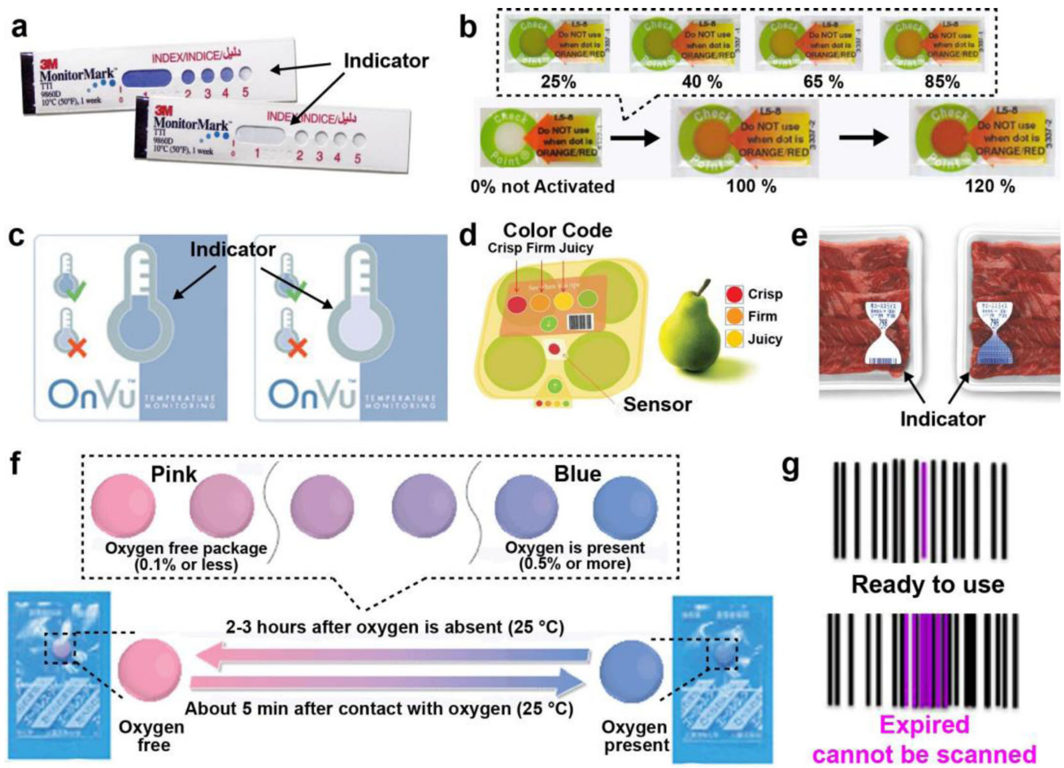

Figure 3. Smart food packaging indicators. (a) Monitor Mark^{TM} by 3M (USA) (http://3m.com); (b) Fresh-Check® by Lifelines Technologies Inc. (USA) (http://fresh-check.com/); (c) OnVuTM indicator by BASF (Germany), Copyright (2014), with permission of Springer; (d) Ripesense® sensor by Plant and Food Research (New Zealand) (http://www.ripesense.com/); (e) OnVuTM by To-Genkyo (Japan) (http://www.to-genkyo.com/); (f) Ageless Eye® oxygen indicator by Mitsubishi Gas Chemical (Japan) (http://www.mgc.co.jp/); (g) Food Sentinel System by SIRA Technologies (USA), Copyright (2017), with permission of Elsevier.

quality, safety, and authenticity of agri-food products will be stored remotely and kept as records for food traceability.

Smart indicators and sensors integration into the food supply chain

Smart packaging is defined as any type of container that is capable of carrying out smart functions beyond a physical barrier between food and their surrounding environment. Currently, microbial contaminations and adulterations are only tested during production and processing, and less frequently during storage and distribution that could lead to subsequent major food outbreaks (Gizaw 2019; Nizar et al. 2018). Smart packaging can overcome this concern by monitoring the environmental conditions inside the packaged foods. To acquire the information of a product across the food supply chain, two types of smart packaging systems have been explored: (1) indicators and sensors in food packaging that allow the collection of information about the environmental changes and condition history of the packed food and (2) data carriers (*e.g.*, barcodes) to store or transmit data for food distribution and traceability.

Smart food packaging indicator

Indicators integrated into food packaging have been extensively applied in the food industry and have achieved successful commercialization. These indicators provide visual and qualitative information to inform consumers the safety and quality of the packaged foods (Ghaani et al. 2016; Kim et al. 2018; Schaefer and Cheung 2018). Despite a large variety of indicators, four types of indicators have been widely developed for food products for temperature, freshness, presence of a gas, and biosensors for the detection of microbes.

Temperature indicator

Temperature indicators are the first type developed and can sense whether food has reached a particular temperature, most commonly, been heated above, or also cooled below a reference temperature. These were among the first types of indicators to aid consumers in identifying the potential risk of microbial growth and protein denaturation during storage and transportation. The indicating events rely on enzymatic, polymerization or biological reactions (Lu et al. 2013; Pereira, de Arruda, and Stefani 2015; Zhang et al. 2013). Commercial products include MonitorMark (3M, USA), OnVuTM (BASF, Germany), and Fresh-Check® (Lifelines Technologies Inc., USA) (Figure 3a–c). Temperature indicators still play a critical role in maintaining the safety and quality of perishable and frozen food products because they are eco-friendly and cost-effective (Zhang et al. 2013).

Freshness indicator

Different from temperature indicators that provide an indirect measure of food freshness in the form of absence of

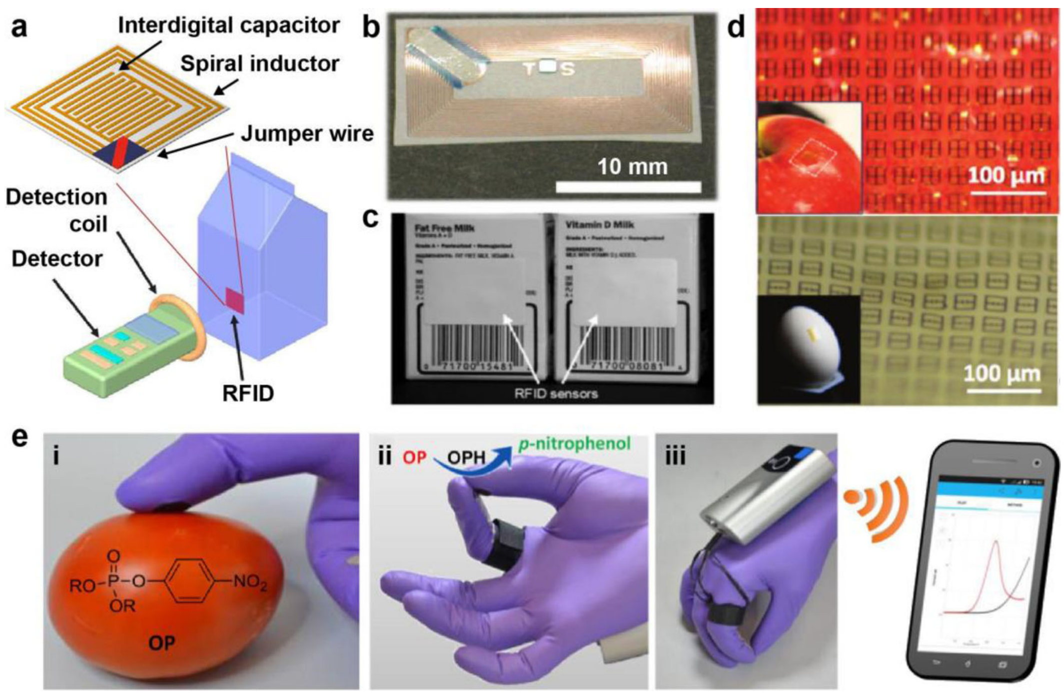

Figure 4. **Wireless detection of food safety.** (a) Schematic detection mechanism of food safety using RFID. (b) Example of the 13.56-MHZ passive RFID tag on a plastic flexible support (Reproduced with permission from ref. (Potyrailo and Morris, 2007), copyright 2007, American Chemical Society). (c) Noninvasive monitoring of two types of milk using disposable RFID sensors that were embedded in milk bottles (Reproduced with permission from ref. (Potyrailo et al. 2009), copyright 2008, John Wiley and Sons). (d) Photographs of silk-based silk sensors on the surfaces of apple and egg (Reproduced with permission from ref. (Tao et al. 2012), copyright 2012, John Wiley and Sons). And, (e) Photographs of the wearable and flexible glove biosensor for the detection of organophosphorus (OP): i. on-glove swiping food surface, ii. on-glove detection of OP by joining the index and thumb finger, iii. wireless transfer of the collected data to a smartphone via bluetooth (Reproduced with permission from ref. (Mishra et al. 2017), copyright 2017, American Chemical Society).

temperature abuse, a freshness indicator provides a direct indicator of microbial growth by measuring microbial metabolites. This type of indicator generally involves a pH-associated color change caused by a reaction of a colorimetric reagent with microbial metabolites. Such a colorimetric approach has been widely used to detect pH-associated metabolites, including volatile nitrogen compounds, amines, organic acids, carbon dioxide, ethanol, glucose, and sulfur compounds (Choi et al. 2017; Li et al. 2019; Tichoniuk, Radomska, and Cierpiszewski 2017). For example, pH-sensitive natural dyes using curcumin, grape peel, and beetroot extracts have been used to measure an increase in pH corresponding to total volatile amines that can represent meat freshness. A similar study was performed to develop a pH indicator film by incorporating agar, potato starch, and anthocyanins (Choi et al. 2017). A commercial product (Ripesense®) for monitoring the ripeness of fruits were developed by the Plant and Food Research (New Zealand) based on a reaction between sensor elements and characteristic aroma compounds such as ethylene (Figure 3d) ("Active & Intelligent Packaging," 2004). Another commercialized freshness indicator for meat products was developed by a Japanese company To-Genkyo (Figure 3e), based on color change caused by the interaction with ammonia release ("TO-GENKYO-TOKYO: Bad Meat Detector," 2009).

Gas indicator

Gas indicators provide information about the presence of a particular gas or the changes in gas content. The gas indicators can determine gases associated with food quality, including oxygen and carbon dioxide. These can also be used to detect package leakages (Jung, Puligundla, and Ko 2012; Lee and Ko 2014; "TO-GENKYO-TOKYO: Bad Meat Detector," 2009; Vu and Won 2014). Gases generated through diffusion into food packaging or from microbial metabolism and enzymatic/chemical reactions in food matrices can often be used to predict food safety and freshness (Mills 2005). A colorimetric indicator, such as methylene blue that can change the color in the presence of a particular gas, is the most common type of gas indicator. Ageless Eye® (Mitsubishi Gas Chemical Company, Japan) is a commercial indicator for monitoring oxygen concentration, where the color of the indicator changes from pink to blue in the presence of oxygen (Figure 3f) (Wang and Wolfbeis 2014). These indicators can be placed inside the package of any food product.

Biosensor indicator

A biosensor can be integrated into a smart packaging to detect the presence of pathogenic bacteria or their metabolites. SIRA Technologies (USA) developed the Food Sentinel System based on an immuno-biosensor carrying an antibody toward a specific pathogen in the form of a membrane attached to the barcode (Figure 3g). This immuno-biosensor system was composed of an absorbent material providing for the directional flow of the target juices, an immunobead solution pad, and a detection area. This indicator integrated into the biosensor turns purple when the food is contaminated by the targeted pathogens. This color change alerts consumers and retailers when the product is exposed to microbial contaminations (Yam, Takhistov, and Miltz 2005). Toxin Guard^{TM} (Toxin Alert Inc., Canada) is another visual diagnostic tool to detect foodborne pathogens based on antibody-antigen reaction on a polymer film (Han 2014). In the presence of a pathogen, the bacterial toxin can generate a visible color change after binding to the antibody that are immobilized on a thin layer of food packaging film. Other than the colorimetric biosensors, fluorescence signals using quantum dots display superior performance to detect nitrite content in meat products (*e.g.*, sausage and beef) and pathogenic bacteria in beverages (*e.g.*, milk and apple juice) (Li et al. 2017; Zhao et al. 2009). Due to the toxicity of biosensing materials and cost-factor, it is still rare to find such a commercial package integrated with a biosensor indicator (Schaefer and Cheung 2018).

Wireless-based detection applications in food safety

Wireless-based detection of food safety relies on a device that can collect information about a food property as well as wirelessly transfer the collected data for further analysis. This technology is particularly suited to food packaging that has a restriction on the device size and energy consumption. Currently, data are transferred to a mobile device via Bluetooth so that aspects associated with food safety, such as a change in pH or temperature, can be analyzed, and then a prediction of safety or remaining shelf-life is determined. Thanks to the development of flexible and self-healing electrodes, wireless-based detection has been applied to monitor food safety in recent years. Without the requirement of additional circuits, the device can wirelessly transfer the collected data in either a passive or active way (Xu, Zhu, and Yu 2017). Due to the advantages of its mobility and ease-of-use, the development of wireless-based detection for food safety is a trend for smart food traceability.

The most widely used passive wireless sensor to detect and track food safety in the food supply chain is based on radio frequency identification (RFID) tags (Potyrailo, Mouquin, and Morris 2008). The detection mechanism using RFID tag is shown in Figure 4a. The passive sensor consisting of an interdigital capacitor and a spiral inductor is usually fabricated on the inner wall of food packaging (Tan et al. 2007). When the capacitance of the interdigital capacitor changes, a hand-hold detection coil that is interrogated with a special resonant frequency of the capacitor can measure the difference. By monitoring the capacitance changes caused by food property (*e.g.*, humidity, conductivity, and oxidation products), the response of a passive sensor can be correlated with specific safety or quality parameters. Potyrailo et al. developed passive 13.56-MHz RFID tags to monitor the spoilage of whole milk and fat-free milk (Figure 4b-c) showing that whole milk had a faster spoilage rate than the fat-free milk (Potyrailo et al. 2009). As shown in Figure 4d, similar RFID tags have been incorporated into the cap of milk bottles and on the surface of foods (*e.g.*, apples and eggs) (Tao et al. 2012; Wu et al. 2015). In another study, Ong et al. developed a remote query resonant-circuit sensor to monitor bacterial growth in food products (Ong et al. 2001). Unlike the passive wireless sensor, an active sensor can send the collected data to receivers by wireless transmission, such as Bluetooth and ZigBee (Kaushik and Singh 2013). Mishra et al. fabricated a flexible and stretchable electrode on gloves to detect organophosphorus residues with data actively transmitted to a smartphone via Bluetooth (Figure 4e) (Mishra et al. 2017). Due to the requirement of power supply in the sensor end, active wireless sensors are less popular.

Wireless-based detection of food safety and freshness sensors enable a more robust traceability across the food supply chain. Instead of relying on periodic testing by quality control personnel within a company or by a governmental organization, companies will be able to use these technologies to identify potential risks and develop science-based measurements to control hazards. For example, wireless technology has also allowed the World Health Organization (WHO) to gain a more comprehensive view of an operation from continuous monitoring that these sensor technologies provide than from periodic inspection, making it possible to establish standards and oversee enforcement. The inherent flexibility can be scaled from a single local site to multi-site operation via on-site testing and remote interpretation of the collected data (Wu et al. 2017).

Data-assisted analysis for foodborne outbreak response

To effectively limit consumer exposure to pathogens during a foodborne outbreak, health authorities attempt to quickly determine the source of contamination, identify contaminated food items, and remove all affected products from the marketplace. These are difficult tasks due to the presence of multiple ingredients in food items, the complexity of food supply chains, and the vast geographic distances across which food products are transported. Therefore, during a foodborne outbreak, three independent streams of evidence are integrated and weighed to support recall actions: (1) laboratory investigation (isolate matching), (2) epidemiological assessment, and 3) food safety investigation (trace-back to implicated lot) (Health Canada 2011). Whole genome sequencing (WGS) coupled with bioinformatic analysis is currently used to detect clusters of cases across borders and at extremely high-resolution, meaning the size and scope of the outbreak can be quickly determined. WGS also allows for isolate matching between the current isolate and the historical counterparts, in some cases this means that a putative geographic source of contamination can be immediately identified without having to access any food supply chain traceability data. However, if WGS data is effectively integrated with smart food traceability data it will allow for rapid identification of associated companies, sources of ingredients, any temperature abuse or potential cross-contamination events, and a list of additional products that may be contaminated. Having both datasets available to investigators will speed the process of identifying and recalling

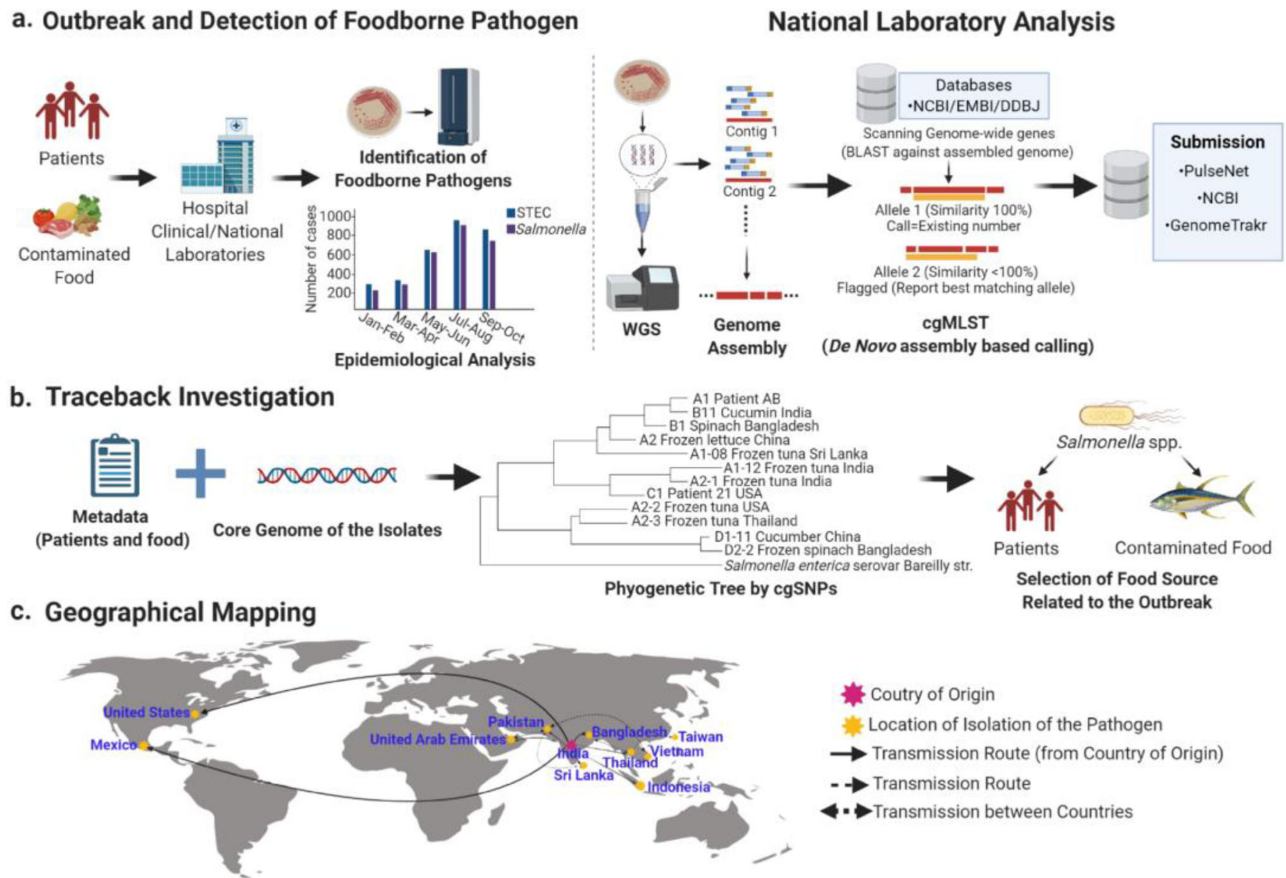

Figure 5. Foodborne Outbreak Response. Traceback investigation of foodborne illness outbreak utilizes both WGS data as well as smart traceability data to rapidly identify the source of contamination and additional food items that may be contaminated. (a) Once a foodborne outbreak occurs local and national laboratories isolate and sequence the etiological agents. Sequence data can be rapidly compared to international databases to identify where closely related strains have been observed in the past. (b) Metadata from patients and food products allow for epidemiological and traceback analysis. (c) The phylogenetic analysis of the isolate can be projected onto a map to reveal the most likely geographic origin for the outbreak strain. Food traceability data can then be used to traceback and trace-forward linked foods to identify other related cases. The figure was created with BioRender.com.

dangerous food items from the market - ultimately making the food supply chain safer.

Short-read sequencers, such as the Illumina MiSeq, are user-friendly at a price point where they can reasonably be distributed to local laboratories, and can produce a quality draft-genome for a bacterial pathogen in a matter of hours (Quainoo et al. 2017). Whole-genome sequences are usually generated by local laboratories and then up-loaded to centralized servers for *de novo* assembly, taxonomic identification, contamination checking, and basic quality assessment (Thompson et al. 2013). A core genome is the set of genes that are present in all strains of a given species. The core genome has been defined by BioNumerics for each common foodborne pathogen, and whole-genome sequences are judged to be of adequate quality if >95% of the core genome is present (Timme et al. 2017). Short-read sequences are assembled to contiguous sequences where each base pair has been independently sequenced 20–100 × and sequencing errors can be corrected. Therefore, only true nucleotide variations are identified. If a sequence is of adequate quality, core genome multilocus sequencing typing (cgMLST) takes place on a centralized server. cgMLST is based on the concept of allelic variation. Single nucleotide polymorphisms (SNP) are identified within each of the core genes and assigned an allelic number. Each strain receives a unique allele code that communicates the phylogenetic relatedness of multiple isolates (Figure 5a) (Tolar et al. 2019). Groups of three or more clinical isolates that have less than 10 allele differences found within the past 60 days (or 120 days for *L. monocytogenes*) are defined as clusters, meaning they are part of the same outbreak and likely originate from the same source (Tolar et al. 2019). This aspect of WGS also improves the epidemiological stream of evidence since more linked patients can be identified and interviewed (Figure 5b). Each whole genome sequence is compared to a PulseNet maintained database that currently hold >125,000 genome sequences, including *Escherichia coli, Salmonella, Listeria, Campylobacter*, and *Vibrio*, in a customized version of BioNumerics (Applied Math, Sint-Martens-Latem, Belgium) (Tolar et al. 2019). This database contains whole-genome sequences from international bacterial isolates originating from clinical, food, factory, and agricultural sources. Based on phylogenetic relatedness to other isolates in the database, local labs are provided with a likely geographic and food source for their clinical isolate (Hoffmann et al. 2016). This technique was successfully used during a 2012 *Salmonella* outbreak in the United States that was linked to spicy tuna rolls, but both the source and ingredient containing *Salmonella* were unclear. WGS and analysis revealed that the isolate in question was a match to a historical isolate from India, which was ultimately identified to be less than 8 km away from the processing plant that sourced the tuna for the rolls (Figure 5c) (Allard et al. 2016; Hoffmann et al. 2016). Whole-genome sequences are then uploaded to either GenomeTrakr or the National Center for Biotechnology Information (NCBI) for long-term safe storage of the data, clinical metadata is anonymized and the sequences are made available to non-PulseNet laboratories (Allard et al. 2016).

Long-read third-generation sequencing can also theoretically be used in surveillance activities and the Oxford Nanopore is an attractive option due to its handheld device, but this is not the optimal sequencing strategy for the purpose of outbreak delineation since the data interpretation techniques used for these investigations are based on SNP calling, which requires a high level of sequence accuracy, and third-generation sequencers are still struggling with an error rate of about 15% (Quainoo et al. 2017; Tolar et al. 2019).

After WGS data has linked a food item to illness, smart food traceability can be used to traceback the companies responsible for growing, packing, importing, and manufacturing the suspected product, which facilitates finding the source of contamination, and trace-forward can identify points of distribution of additional products that may also be affected until all affected products have been identified. Continued improvement in this area will come from finding ways to more effectively integrate data from each stream of evidence. In addition, increased availability of whole genome sequences in centralized databases for accurate comparison will aid in identifying the source of contamination in outbreak events. As the sequences of international environmental and agricultural isolates are uploaded, food and geographic mapping will become increasingly accurate. In addition, improved accuracy in the third-generation, handheld, sequencing devices will facilitate more widespread sequencing efforts that will aid in populating databases with food and agricultural isolates from developing countries.

Strategies for tackling big data in food traceability systems

E-commerce has significantly shifted consumer's grocery shopping styles. More and more consumers will likely be clicking on carts rather than rolling them through the aisles. In 2015, both Amazon PrimeNow and Google Express have expanded into the same-day grocery delivery along with a number of national and regional grocery stores. This has created new challenges for the food industry in support of e-commerce for food delivery. Meanwhile, a ton of data about food safety and quality in the food supply chain has been created. However, little attention has been paid to the collection and utilization of the data for food safety. Food traceability system is highly data-based as a huge amount of data on food products is collected from different critical control points of the food supply chains, including harvest, transportation, storage, processing, and distribution.

Data of food traceability systems have the characteristics of big data that are of high volume, high rate of input, and heterogeneity (Kitchin and McArdle 2016; Moldes et al. 2017). Big data is an emerging concept to describe data that are too much, fast, and complex to be managed, visualized, and analyzed using the conventional technologies. Most of them are unstructured data that do not follow a specific data model (Mahmood 2016). With the advancement in Internet-of-Things (IoTs) blockchain technology, more data on food can be transmitted and processed in real-time (Galvez, Mejuto, and Simal-Gandara 2018). So far, computer scientists have developed dynamic frameworks (*e.g.*, Hadoop and Spark) to process big data at the aspect of volume dimension, yet they are not adequate to handle fast and heterogeneous data (White 2012). Nevertheless, the big data scenarios in food traceability systems, if not well handled, will largely prolong the time to identify the sources of food contamination when food incidents occur.

IoTs allow things and objectives to be connected anytime and anywhere. It is growing exponentially and will become popular in the food safety domain. Thanks to the rapid development of multipurpose sensors and wireless transmission in the food supply chain, IoTs will be a great technique to analyze these data, providing more information than the conventional food inspection technologies to improve food safety (Popa et al. 2019). To effectively use these data, machine learning technologies (*e.g.*, deep learning and neural networks) are highly demanded. There are five layers in IoT architecture including the device layer, network layer, service support layer, application layer, and management and security (Bouzembrak et al. 2019). Both the device layer and network layer have been studied in the last decades, but the service support layer and application layer focusing on data processing, data storage, and specialized applications are still in their infancy. New technologies based on IoTs can bring safer, more efficient, and sustainable food supply chains. For example, Smiljkoviki et al. built an IoTs-based system named SmartWine to manage resource consumption and prevent disease in the wine supply chain (Astray et al. 2019; Smiljkovikj and Gavrilovska 2014). Shih et al. developed a real-time remote monitoring system to track the temperature in a cold supply chain (Shih and Wang 2016). Chen et al. constructed a smart cold chain system to track food freshness (Chen, Wang, and Jan 2014). In summary, IoT technology applied in the food supply chain can aid in managing big data in smart food traceability systems.

Another important technique to address the big data issue in food traceability systems is cloud computing, which is defined by Gartner as "a style of computing where scalable and elastic IT-enabled capabilities are delivered as a service to external customers using Internet technologies" (Plummer et al. 2008). Cloud computing enables users to perform complex computation without the expense of maintaining costly hardware and software. This technology provides three main types of computational services over the Internet: (1) infrastructure as a service (IaaS) that offers virtualized computing resources including computation and data storage services; (2) platform as a service (PaaS) that provides developers a platform to frame customized applications; and (3) software as a service (SaaS) that delivers applications to the users (Shakhovska 2017) Among them, SaaS is the most frequently used service, which is often served on a pay-as-per-use basis by a third-party vendor. Cloud computing integrated with IoT creates IoT-as-a-service (IoTaaS) that offers computing resources to IoT devices in food traceability systems, such as sensors, actuators, and portable detection devices (Hwang, Dongarra, and Fox 2013). Cloud computing technology helps store, share, manage, and analyze the data from food sensors and identifiers, which are accumulated along with the movement of food in the supply chains. It also assists in the on-site analysis of data from portable food detection devices by allowing the users to run data analysis applications via a web browser over the Internet. However, users in remote and low-infrastructure areas may confront network limitations, thereby restricting their use of IoTaaS for food traceability purposes. In this scenario, emerging wireless networks play a key role in building the connection between IoT and the required cloud computing services. Particularly, the fifth-generation (5G) network as a new generation mobile technology has more bandwidth, enables real-time data transfer with low latency, and supplies gigabit connections without location restrictions. It will prompt the automated data collection from IoT and data analysis through IoTaaS in the food traceability systems in future (Mavromoustakis, Mastorakis, and Batalla 2016).

Conclusion

There is a critical need to develop a smart food traceability system that can improve food safety, reduce foodborne outbreaks, and ensure food security. Ideally, this system is relying on risk-based controls, such as those underlying FSMA and driven by advanced technologies. Integrating IoTs and cloud computing into food safety detection technologies will help develop such a smart food traceability system. This review provides a blueprint outlining critical steps to follow the ever-changing global food supply chain. In addition, it helps readers understand the current technologies for food safety detection and sense the potential of emerging digital technologies for its potential applications in agri-foods. In the future smart traceability system, the sensors and indicators integrated into the food supply chain will provide more traceability data, which can be analyzed with IoTs and cloud computing to investigate foodborne outbreaks. Future studies will focus on designing and building specific smart food traceability systems for various food supply chains based on tailored IoTs, cloud computing, and sensing technologies. Tons of data collected from critical control points in food supply chains can be shared through the internet to the cloud server for real-time analyses.

Disclosure statement

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