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Progress towards achieving intelligent food assurance systems

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A R T I C L E I N F O

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A B S T R A C T

Background: Food assurance systems (FAS) that are critical for protecting the quality and safety of food products can be defined as a systematic approach to ensuring the safety, quality, and authenticity of food products, from the initial production stage to the final consumption by the consumer.

Scope and approach: An Intelligent Food Assurance System (IFAS) is a proposed system that would have the ability to use intelligent sensors, data processing systems and other advanced technologies to detect and control the quality and safety of food. This review provides an overview of the current state-of-the-art in food assurance systems, with a focus on the four components of food assurance: food quality, food safety, food authenticity, and food defence. An initial review of the scientific literature on food assurance was conducted in order to clarify their definitions and connections. This review provides a synopsis of the fundamental concepts and definitions of a FAS, followed by a comprehensive review of recent advancements in smart food technology, such as precision agriculture systems, remote sensors and smart food management systems that would be required for an IFAS.

Key findings and conclusion: A critical analysis of the challenges when building an IFAS, and potential future directions are also discussed. Furthermore, the possible influence of an IFAS on enhancing transparency and traceability in the food chain, reducing loss and waste for sustainable development, and improving consumer confidence is highlighted.

1. Introduction

1.1. Context

Food is essential for human life, providing the necessary energy and nutrients for vital activities. Therefore, it is important that systems and processes are adopted that can assure that food produced for the consumer is safe. Food assurance is more than ensuring safety, it can also be used to ensure the quality and authenticity of food. Food assurance usually includes strict testing, monitoring and control measures based on special requirements or standards to prevent food threats. There are various definitions to distinguish between different types of food-related threats: food safety incidents result in unintentional harm; food quality issues are often related to consumer satisfaction; food fraud involves intentional deception for financial gain; and food defence incidents entail intentional harm (Spink & Moyer, 2011). In a world where food threats circulate in complex food networks, systematic food assurance measures are critical to preventing foodborne illness and protecting the health of consumers. This review uses the term food assurance to summarise activities that assure consumers and businesses that food production meets specific standards, based on the four types of issues that threaten the integrity of the food chain as described. To ensure the integrity of the food chain, it is essential to anticipate, defend against, and intervene in such problems to achieve food assurance. The environment in which food security functions is constantly changing, with new challenges such as climate change, emerging pathogens and supply chain disruptions highlighting the need for adaptable and flexible Food Assurance systems (FAS). Therefore, this review focuses on exploring FAS that encompass food quality, food safety, food authenticity, and food defence and how the use of state-of-the-art intelligent technologies can be incorporated.

With technological advances leading to the generation of vast amounts of data, the field of data science has emerged as a means to extract insights from such data. Data science is often described as the "next big thing in innovation" and the fourth paradigm of science, and its widespread use has had a significant impact on the development of intelligent systems (Chiang et al., 2017; Gobble, 2013; Klerkx et al., 2019). In the food industry, intelligent technologies such as IoT and Big Data offer opportunities to efficiently process large amounts of data, thus enabling more efficient and intelligent food safety protection (Lei

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et al., 2022; Misra et al., 2022). Traditional methods, although widely used in industry, may struggle to keep pace with dynamic challenges. It is in this context that Intelligent Food Assurance Systems (IFAS) may have greater potential. Leveraging advances in smart technologies and data analytics, IFAS can have the potential to improve food safety, quality and authenticity through real-time monitoring, predictive analytics and traceability, while also navigating the intricacies of the modern food supply chain.

By providing a comprehensive review of FAS, this research aims to identify key benefits, opportunities and limitations of food systems, and potential solutions to existing problems. Exploring the current state of intelligent food systems aims to drive the development of more robust and efficient IFAS to improve cost-effectiveness, resource utilisation, and food chain integrity.

1.2. Related definitions

1.2.1. Food quality, safety, authenticity, and defence

Food quality and safety are crucial aspects for the food industry (SSAFE, 2023). The World Health Organization (2018) estimated that foodborne illnesses cause nearly one in ten illnesses worldwide each year. Food safety hazards can be categorized into seven groups: microbiological contamination of food, chemical contamination of food, adulteration of food, mislabelling, misuse of food additives, genetically modified food, and expired food (Gizaw, 2019). Additionally, food allergies and mixed toxicological hazards are significant safety concerns (Borchers et al., 2010). While the definition of food quality has evolved over time, it is generally perceived as a combination of intrinsic and extrinsic characteristics that meet the needs and expectations of consumers. Becker (1999) described it as the combination of extrinsic qualitative quality (perceived quality) and intrinsic quantitative quality (measurable quality). Similarly, Grunert (2005) defined quality as the physical characteristics of a product and its subjective perception by the consumer. Food authenticity is another concern that has gained attention in recent years. Popping et al. (2022) used the term "food inauthenticity" to describe food problems where the motivation may be intentional, unintentional, or unknown, thus presenting the food in an inauthentic state. The concept of food fraud is defined as the deliberate and intentional act of deceiving consumers for economic gain using food (Elliott, 2014), which is a category of intentional behaviour resulting in food inauthenticity. Spink et al. (2019) provided a detailed definition of food fraud as the use of food to illicitly deceive for financial gain including the deliberate and intentional substitution, addition, alteration or distortion of food, food ingredients or food packaging; false or misleading representations about a product for financial gain. Unlike food safety, which primarily focuses on unintentional contamination, food fraud is a malicious act that may result in the consumption of unsafe or harmful food. Food fraud can occur at any stage of the food supply chain, from raw materials to final products, and it can involve various types of fraudulent activities as indicated (Spink & Moyer, 2011). Food defence, also known as food protection, is defined as "the protection of food products from intentional contamination or adulteration by biological, chemical, physical, or radiological agents, and the prevention of the introduction of such agents into the food supply" by the U.S. Food and Drug Administration (FDA) (Nutrition C. for F. S. and A., 2022, October 5).

1.2.2. Food assurance

In the UK, the Food Standards Agency described food assurance schemes as activities that help provide assurance to consumers and businesses that food production meets specific standards (FSA, 2018). Spink and Moyer refered to food defence, food fraud, food safety and food quality as the four elements of a food control system or food protection (Spink & Moyer, 2011). To better understand this food assurance, the food risk matrix can be used to visualise the differences between food issues (Spink & Moyer, 2011). Fig. 1 illustrates that the

Fig. 1. The food protection risk matrix.

four components have different emphases: Food quality focuses on subjective consumer values; food safety focuses on unconsciously generated health risks; food defence focuses on conscious food contamination; Food authenticity focuses on economically motivated adulteration, which may or may not render food harmful to health (Manning & Soon, 2016). Food Assurance outlines activities that assure consumers and businesses that food production meets specific standards, based on the four categories of issues that threaten the authenticity and integrity of the food chain. It is important to emphasise that although the causes or motivations for the four food issues mentioned are different, the effects often threaten the environment and human public health.

1.2.3. Food assurance systems

In food assurance activities, quality assurance likewise has a broad definition, whereby Manning et al. (2006) argued that quality assurance models must address food safety, product quality and organisational standards in order to deliver safe, consistent food in a financially viable food chain. Krystallis et al. (2006) saw food quality assurance schemes, along with geographical indication protection and organic certification, as the cornerstones of the European food quality policy, addressing motivated, quality-conscious consumers as the central objective of any food quality assurance policy. To protect food authenticity, food companies must implement a comprehensive food fraud prevention system, which involves identifying and assessing potential risks, establishing control measures, monitoring and verifying the effectiveness of the system, and continuously improving the system. This also allows for the detection of contamination, adulteration and verification of the authenticity of food products (Marcone, 2012, pp. 26–38). This is coupled with advanced analytical techniques to ensure food authenticity and food defence, such as the use of analytical methods such as DNA testing, chemical analysis and spectroscopic analysis, which can identify the authenticity and quality of food ingredients and products (Candoğan et al., 2021; Danezis et al., 2016).

It follows that a robust FAS is crucial to protect public health and ensure the integrity of the food supply chain. A FAS is the cornerstone of ensuring the safety, quality, authenticity and reliability of food in the intricate food chain, which can be defined as systematic approaches to ensuring the integrity of food products, from the initial production stage to the final consumption by the consumer. It encompasses the range of concepts, including food quality and safety, food fraud prevention, and food defence. These systems encompass a wide range of practices, standards and technologies, including the implementation of food safety management systems such as HACCP, VACCP and TACCP, Food Fraud Vulnerability Assessment (FFVA) (Alrobaish et al. (2021), regular testing of products, and continuous monitoring of supply chains. In recent years, the integration of advanced technologies has ushered in a new era for food systems. Progressing technologies have revolutionised all aspects of the food industry, especially innovations such as precision agriculture and artificial intelligence, which have led to new ways of growing, processing, distributing and consuming food. An IFAS represents a comprehensive approach to ensuring food safety, quality, authenticity and defence through the integration of advanced technologies. These systems leverage the latest developments in sensors, data analytics, blockchain, artificial intelligence (AI), and the Internet of Things (IoT) to provide real-time monitoring and management of the food supply chain. Subsequent chapters will detail the specific applications and roles of these advanced technologies under each of the supply chain sections. As the food industry moves deeper into this new era, IFAS will have multiple possibilities for further innovation and improvement using smart technologies. As the vision for an IFAS, Fig. 2 visualises the data flows and processes that would underpin the operation of an IFAS across the various components of the food chain, describing how the information would be collected, analysed and utilised, and highlighting the role in improving transparency and traceability.

1.3. Purpose of the review

The purpose of this review was to explore the emerging technologies suitable for use in the food supply chain and their potential for developing an IFAS. The review focused on the current status of precision farming systems, laboratory analysis, and the application of a FAS to improve food quality, safety, authenticity and defence. Highlighted herein are the significant advances in technology, particularly in the areas of digital science, food testing, and other technologies that are providing the foundation for creating more efficient and reliable food safety systems.

2. Existing food assurance systems

2.1. Food risk assessment

Food risk assessment involves the identification of a hazard and the systematic characterisation of systems and failures that may contribute to that hazard and consists of four steps as shown in Fig. 3: hazard identification, exposure assessment, hazard characterisation and risk characterisation to analyse the risk to healthy life arising from exposure to biological, chemical or physical hazards in food (Ross & Sumner, 2002). There are two general approaches to risk assessment; qualitative risk assessment is a descriptive or categorical treatment of information, while quantitative assessment is a mathematical analysis of numerical data (Krystallis et al., 2006). The initial phase of a formal risk assessment involves hazard identification, which is a qualitative evaluation of potential risks and an initial review of the data that will be analysed in later stages of the assessment. In established fields of risk assessment, such as

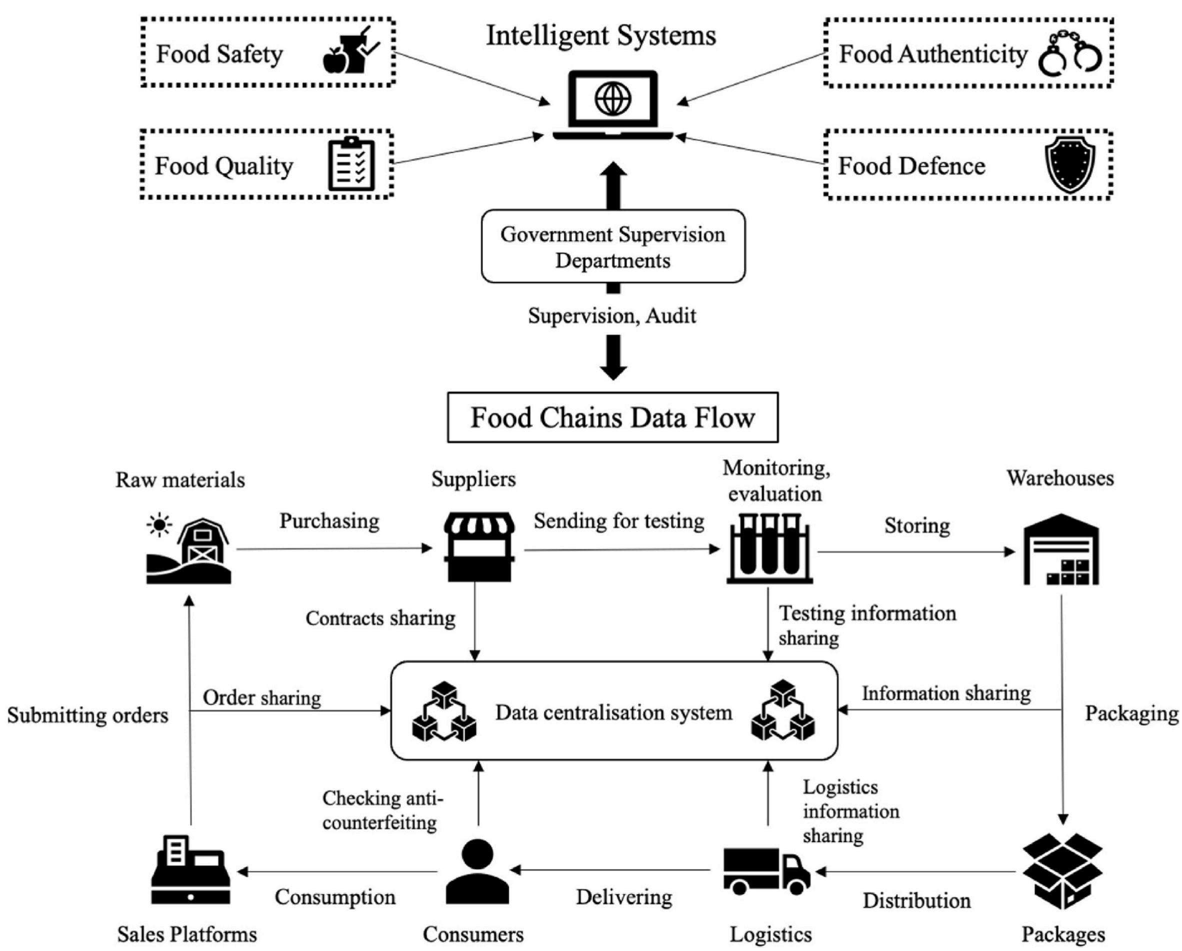

Fig. 2. The vision of IFAS.

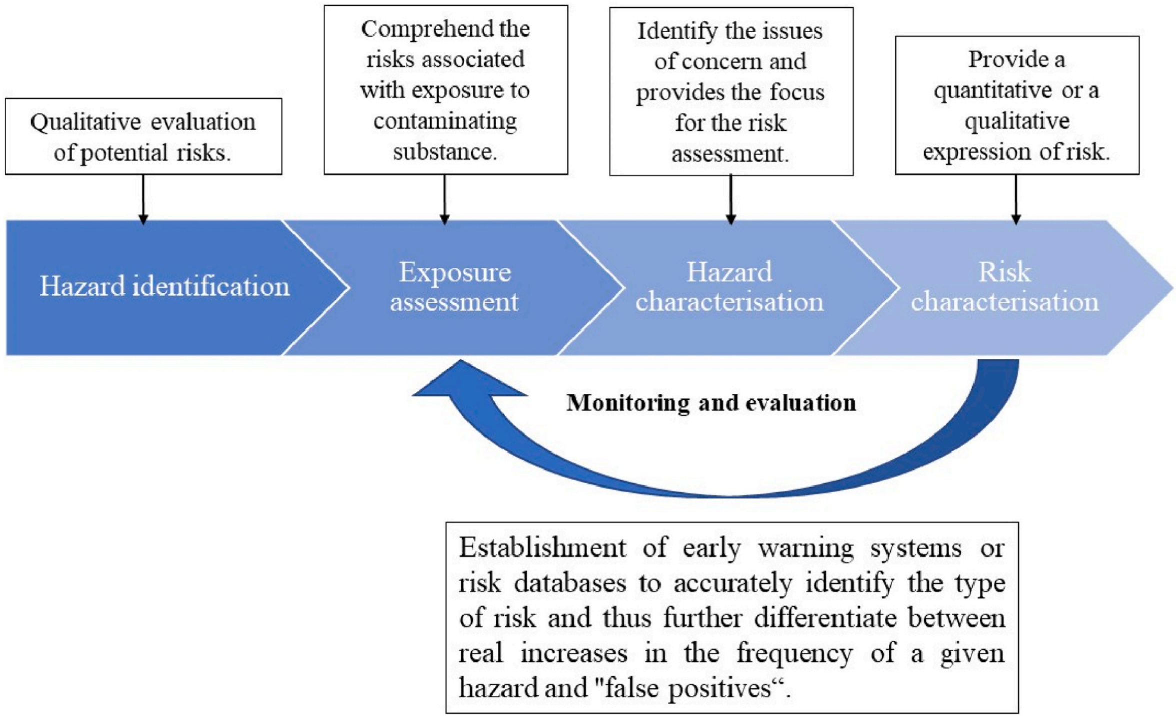

Fig. 3. Food risk assessment process.

environmental health and toxicology, the primary aim of hazard identification is to establish whether there is substantial evidence to suggest that a substance, such as a chemical, could cause adverse health impacts like cancer (Lammerding & Fazil, 2000). Exposure assessment plays a critical role in comprehending the risks associated with exposure to both naturally occurring and non-naturally occurring toxic substances, such as aflatoxins in food, radon in the air, benzene in groundwater, methyl *tert*-butyl ether in the air, and food additives (Paustenbach, 2000). Hazard identification identifies the issues of concern and provides the focus for the risk assessment. The exposure assessment generates estimates of the likelihood and magnitude of exposure to hazards and provides the basis for the next two assessment steps, hazard characterisation and risk characterisation, in which the exposure output is translated into risk measures (Lammerding & Fazil, 2000). Ross and Sumner present a simple, spreadsheet-based tool for food safety risk assessment, which combines qualitative and quantitative inputs to generate indices of public health risk (Ross & Sumner, 2002). The Rapid Quantitative Microbial Risk Assessment (sQMRA) tool developed by Evers and Chardon is a simplified QMRA model developed for assessing public health risks from pathogen-food combinations, which helps to quickly obtain relative risk estimates (Evers & Chardon, 2010). In silico techniques such as quantitative structure-activity relationships (QSAR) models are also developed for drug and chemical information in order to comprehend the correct mechanisms underlying diverse agrochemical and food activities (Kar et al., 2017). By identifying potential hazards and estimating their risks, food safety authorities can take appropriate measures to protect consumers from foodborne illnesses, prevent outbreaks, and ensure the safety and quality of the food supply. For detection and assessment, the establishment of early warning systems or risk databases that combine monitoring data with other data on the hazard of interest or the product affected by the risk allows risk professionals to accurately identify the type of risk, thus further distinguishing between true increases in the frequency of a given hazard and "false positives" (Marvin et al., 2009). Food assurance requires a more holistic approach to food risk management for early identification of emerging food safety issues, involving stakeholders other than risk managers and risk assessors, as well as input data from sectors outside the food production chain.

2.2. *Responsibility assessment (HACCP, VACCP and TACCP)*

2.2.1. *The hazard analysis and critical control point (HACCP)*

The HACCP system was developed in the 1960s by Pillsbury in collaboration with NASA and the US Army Laboratory to ensure food safety for astronauts on space missions, using a systematic and proactive approach to identifying, assessing and controlling food safety hazards (Weinroth et al., 2018). It is widely recognized that HACCP is an effective and rational preventive approach that significantly enhances food quality and safety (Bennet & Steed, 1999). The 7-step process of HACCP is visible in Fig. 4 (Notermans et al., 1995). Wang et al. (2008) presented a survey on consumer awareness, willingness to pay, and price premiums for milk products produced using the HACCP management system that demonstrated the potential of this quality management approach in mitigating food safety risks by enabling effective control of critical control points along the food chain. El-Hofi et al. (2010) further demonstrated that HACCP allows for the successful management of risk factors at critical control points, leading to the elimination or reduction of food safety risks. While the application of the HACCP system is known to improve food safety, its effectiveness in preventing foodborne illnesses hinges on its correct application and integration with other food safety management systems, including the provision of hygienic infrastructure and the application of principles of good hygiene practice (Motarjemi & Käferstein, 1999). The implementation of the HACCP system in the food world to date had a profound impact on food safety and to some extent on public health (see Fig. 4).

As a well-established analysis system, HACCP can serve as the foundation for the establishment of an IFAS that are oriented towards risk analysis-based food assurance. Thus, the implementation of IFAS can provide a proactive approach to food assurance, enabling food industry stakeholders to take pre-emptive measures to prevent food safety issues and improve the overall food quality.

2.2.2. *Threat assessment critical control points (TACCP)*

TACCP is a food defence strategy that helps to identify and manage

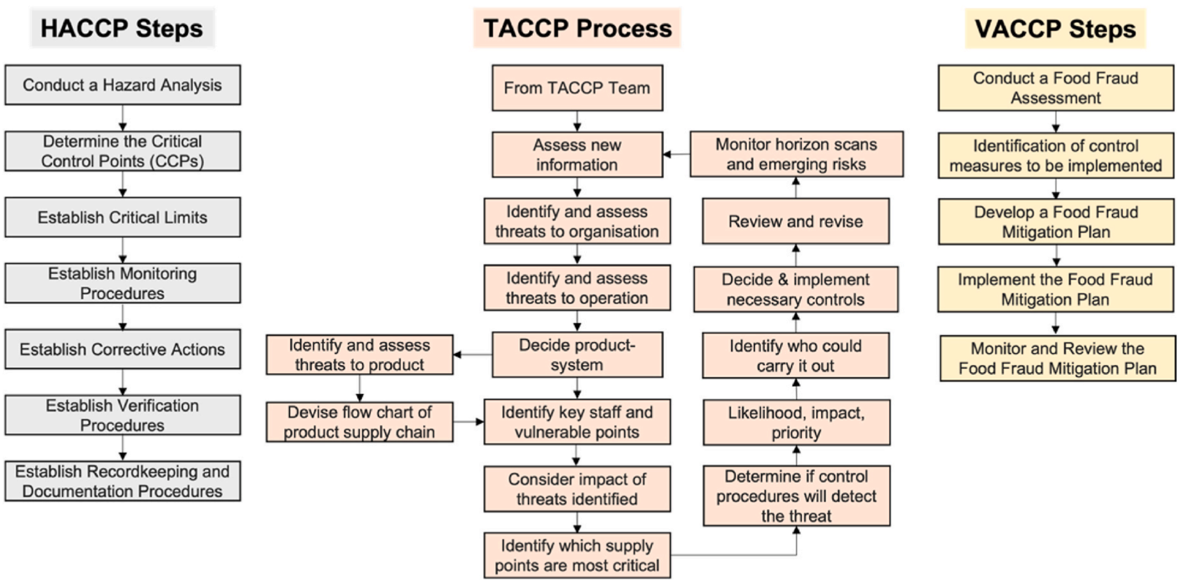

Fig. 4. HACCP, TACCP, VACCP diagrams.

potential threats to the food supply chain. In the UK, TACCP is based on PAS96:2014 (Wareing & Hine, 2016), which is jointly sponsored by DEFRA (Department for Environment, Food & Rural Affairs) and the FSA, and produced by the British Standards Institution. The TACCP process is described in PAS 96:2017 as in Fig. 4 (BSI British Standards institution, 2020). TACCP involves a risk assessment process to identify vulnerabilities in the food supply chain, from the raw materials used to the finished product, with the aim of preventing any intentional or unintentional contamination or tampering with the food at any stage of the supply chain. TACCP considers threats from both internal and external sources, including suppliers, employees, customers, and even criminal organisations.

Several studies have been conducted on TACCP, highlighting its importance in addressing how to combat fraudulent activity in the food industry (Brooks et al., 2021; Manning & Kowalska, 2021). The study by Soon et al. (2019) investigated the use of anti-fraud tools within the UK food industry, emphasizing the importance of proactive measures to prevent fraud. The study concludes that implementing anti-fraud measures such as TACCP can help food companies identify and manage risks throughout the supply chain, ensuring the safety and integrity of their products. Di Pinto et al. (2019) highlighted the importance of TACCP in ensuring the safety and authenticity of food products sold online by assessing Italian PDO cheese and meat products and drawing attention to the risks faced by e-commerce consumers. These studies demonstrate the growing awareness and concern around intentional food contamination and food fraud, as well as the need for effective risk management strategies and tools to ensure the safety and authenticity of food products. TACCP can be an important tool for ensuring food protection and an effective complement to HACCP, helping food companies to identify and manage potential threats throughout the supply chain (Małgorzata, 2015).

2.2.3. Vulnerability Assessment and Critical Control Points (VACCP)

Vulnerability Assessment and Critical Control Points (VACCP) is a food authenticity strategy that focuses on identifying vulnerabilities in the food supply chain that could be exploited by intentional adulteration or other malicious acts. Since its introduction, VACCP has been widely adopted in the food industry as a key component of a comprehensive food protection plan. Few descriptions of the VACCP steps can be found in the academic literature, but the industry can use workflow automation software to implement VACCP as shown in the steps in Fig. 4 (Muscad, 2022). Fox et al. (2018) conducted a mapping of the UK seafood supply chain and identified its complexity, involving numerous stakeholders, making it susceptible to intentional contamination. In response to this vulnerability, they suggested employing VACCP to control access to food production areas and to ensure that only authorized personnel are responsible for handling food. Meanwhile in Europe, Di Pinto et al. (2019) evaluated Italian PDO cheese and meat products to verify their specifications, food labelling and compliance with European Community requirements, and they recommended the VACCP as a key component of a comprehensive food protection programme to prevent intentional contamination of food.

VACCP is seen as a useful tool for assessing the risk of intentional contamination in the food industry. It provides a systematic approach to identifying vulnerabilities and assessing the potential impact on food safety. The food industry has an ongoing need for a comprehensive, context-specific risk management approach to ensure food safety, quality and authenticity (Notermans et al., 1995). Both VACCP and TACCP can be used as a more complete complement to HACCP as a food defence strategy.

2.3. Food fraud vulnerability assessment (FFVA)

Food fraud vulnerability assessment (FFVA) is a tool that is used to assess the vulnerability of a food product to authenticity. The FFVA is based on the routine activities theory and the “design rules” used in developing diagnostic tools for Food Safety Management System (FSMS) assessment (Kirezieva et al., 2013). Though mainly for food fraud, the same "design rules" can be applied to the construction of FAS, using FFVA as a reference for identifying food problems. It focuses on opportunities, motivations, and control measures, and uses a scoring system to develop spider web diagrams that depict the profiles of fraud vulnerability. However, economically motivated adulteration (EMA) poses a unique challenge compared to other food safety risks, as it cannot be easily predicted through traditional risk assessments and intervention strategies (Everstine et al., 2013). To address this, FFVA focuses on systematically identifying and evaluating the factors that create vulnerabilities in the supply chain, where food fraud is more likely to occur. Manning and Soon described the difference between a risk assessment and a vulnerability assessment i.e. vulnerability is a measure of the sensitivity of a system to a threat scenario; whereas the risk level focuses on the consequences and their severity if the threat has materialized (Taylor & Kane, 2005). As a result of increased awareness of food risks, several initiatives have been developed by various organisations to analyse the risk of food fraud and to assess it through the FFVA tool. The formula used by the FFVA is: opportunities x motivations x control measures = actual fraud vulnerability (Motarjemi & Käferstein, 1999). The terms "risk" and "vulnerability" are used interchangeably, and vulnerability is defined as a physical feature or operational attribute that renders an entity open to exploitation or susceptible to a given hazard. The tool was tested and adapted based on multiple workshops with representatives of global food industry actors. The FFVA consists of 50 indicators as shown in Table 1, each with an associated question and corresponding assessment grid, enabling companies to determine the actual status of key risk factors related to opportunities, motivations and controls, thus providing an overall overview of their fraud vulnerability (Silvis et al., 2017). As food fraud is dynamic and pervasive, its prevention requires a continuous effort involving multiple players throughout the food supply chain (van Ruth et al., 2017). This approach not only helps companies to control food fraud, but also promotes an understanding of its root causes and can be applied to the entire food industry chain and actors, allowing for ongoing research and comparison of fraud drivers, enhancements and associated controls.

Table 1
Indicators and their numbers for the three key elements of opportunity, motivation and control measures used in FFVA.

Horizon scanning for opportunities	Knowing networks for motivations	Control measures, staying ahead of the HACCP/VACCP/TACCP
1. Complexity of adulteration raw materials	12. Supply and pricing raw materials	31. Price asymmetries
2. Availability of technology & knowledge to adulterate raw materials	13. Valuable components or attributes raw materials	32. Fraud monitoring system raw materials
3. Detectability adulteration raw materials	14. Economic conditions own company	33. Verification of fraud mon. system raw materials
4. Availability of technology & knowledge to adulterate final products	15. Organizational strategy own company	34. Fraud monitoring system final products
5. Detectability adulteration final products	16. Ethical business culture own company	35. Verification of fraud monitoring system final products
6. Complexity of counterfeiting	17. Criminal offences own company	36. Information system own company
7. Detectability of counterfeiting	18. Corruption level country own company	37. Tracking and tracing system own company
8. Production lines/ processing activities	19. Financial strains supplier	38. Integrity screening own employees
9. Transparency chain network	20. Economic conditions supplier	39. Ethical code of conduct own company
10. Historical evidence fraud raw materials	21. Organizational strategy supplier	40. Whistle blowing own company
11. Historical evidence fraud final products	22. Ethical business culture supplier	41. Contractual requirements supplier
	23. Criminal offences supplier	42. Fraud control system supplier
	24. Victimization of supplier	43. Mass balance control. supplier
	25. Corruption level country supplier	44. Tracking and tracing system supplier
	26. Economic conditions sector	45. Social control chain network
	27. Criminal offences customer	46. Fraud control industry
	28. Ethical business culture sector	47. National food policy
	29. Historical evidence branch of industry	48. Law enforcement local chain
	30. Level of competition in sector	49. Law enforcement chain network
		50. Fraud contingency plan

Collectively, HACCP (TACCP and VACCP) focus on ensuring food safety by preventing or eliminating physical, chemical and biological hazards; FFVA, although similar to VACCP, focuses on identifying weaknesses the system for food fraud and developing measures to address these weaknesses; Food risk assessment is an important tool in ensuring food safety as it helps to identify potential hazards and assess the risks associated with them. Implementing FFVA can be challenging because it lacks the inclusive, transparent, collaborative, and consensus-driven approach that is inherent in the Codex process (Barrere et al., 2020). Currently, as FFVA aims not to detect fraud but to assess vulnerabilities to it (Spink, 2019), VACCP's alignment with established frameworks like HACCP renders it a more suitable choice for addressing supply chain vulnerabilities. The selection between these tools depends on their integration with an organization's existing safety and regulatory practices. These systems are each tailored differently and can be used simultaneously to develop risk management strategies and controls to prevent or mitigate the risks associated with hazards (Barrere et al., 2020).

3. Progressing technologies in the food supply chain

Progressing technologies include a wide range of digital tools such as data mobility and big data analytics, blockchain technology, the IoT and cloud computing. These technologies are beginning to reshape the operations of most companies, improving collaboration and facilitating the development of new business models designed to increase company profitability. The adoption of digital food assurance solutions can even facilitate the creation of digital ecosystems that enhance coordination between various parts of the supply chain, including external partners, the development of collaborative inter-organisational practices, strategies and processes with these partners, and synchronised production processes (Stevens & Johnson, 2016). This section will introduce progressing technologies, which are already available or will be available in the future for application in FAS, together with a discussion of the methods that can be used to build an IFAS. These technologies can be broadly categorized into three parts according to the supply chain process, i.e., the food and agricultural production side, the food analysis side, and the data analysis side.

3.1. Progressing technologies for agricultural production

The global population is growing rapidly and, as a result, the demand for food is increasing. Both agricultural and aquaculture production are needed to meet this demand, but with limited resources with urbanisation such as land, water and labour, more efficient and sustainable agricultural practices are required. Emerging technologies in agriculture, such as precision farming, vertical farming, remote sensing, drones and robotics, have the potential to change the way traditional agricultural production is carried out (Shin et al., 2023). Precision agriculture (PA) is an approach designed to optimise the use of agricultural resources to minimise waste and increase productivity, and through the use of advanced technology and data analysis, precision agriculture can help farmers make more informed decisions about crop and animal management (Yost et al., 2017). In having state of the art data collection systems at farm level this forms the basis for the farm to fork digital traceability framework. By discussing novel sensing technologies for plant monitoring and plant-environment interactions, Lo Presti et al. (2023) argued key functions for wearable sensors, biosensors, and nanotechnology in the upcoming era of digital farms and precision agriculture. In time other data parameters could be incorporated at the farm level accounting for climatic factors and short-term and long-term sustainability.

Emerging technologies for land and farm are influencing the way agricultural production is carried out, improving productivity, sustainability and resilience. The emergence of advanced tools and systems, driven by artificial intelligence, the IoT and other cutting-edge technologies, is fundamentally changing traditional practices. From remote sensing and geo-referencing to smart sensors and autonomous machines, these technologies are ushering in a new era of precision farming. The following Table 2 list the technologies used for land and farm respectively. At the same time, smart technologies for livestock farming play a role. As shown in Table 2, specific technologies for livestock management include Precision Livestock Farming (PLF) and other technologies that help monitor livestock behaviour, early disease detection, reproductive management, herd location tracking and securing food.

Although the agricultural production process is now mechanised and computerised, the lack of digitisation and intelligence is a major obstacle to the improvement of automation capabilities, and the supply chain management of agricultural products is not intelligent enough at this stage (Liu et al., 2021). By taking advantage of these technological advances, the agricultural sector is being equipped with real-time, accurate data that is useful for informed decision-making, resource optimisation and promoting crop and livestock health. These technologies offer a wide range of capabilities, from monitoring livestock behaviour to facilitating early disease detection and breeding management. Advanced systems such as drones and artificial intelligence provide herd location tracking and comprehensive health monitoring. In addition, they can promote improved livestock health and productivity, leading to sustainable and profitable farming operations.

3.2. Progressing technologies for food industry

Food assurance can require rapid, on-line or on-site methods that can be integrated into the management system in order to identify problems within the plant before they become incidents within the food system as a whole. Jagtap and Rahimifard (2019) conducted a case study that examines the implementation of an IoT-based real-time digital firmware tracking system in a food factory, which was utilised to monitor food waste along the production line, resulting in enhanced resource efficiency and financial advantages. Through the systematic monitoring of food waste across different stages of production, the factory can expeditiously detect and address inefficiencies, spoilage, and manufacturing process-related concerns. The prompt identification of such issues is of utmost importance in order to prevent their escalation and subsequent impact on the broader food system, ultimately bolstering food security. Intelligent production control system developed by Konur et al. (2021) offer a novel data collection mechanism and intelligent decision support, and has been successfully integrated with the company's existing equipment and machinery. By predicting and controlling the production line to achieve product consistency, ensure product quality, and increase productivity, the system has enhanced performance and profitability. Hyperspectral sensors can be deployed on different platforms, such as satellites, aircraft, drones and proximity platforms, to acquire images with different spatial and temporal resolutions, and are commonly used to check crop growth with the aim of improving crop yields (Lu et al., 2020). Hyperspectral imaging (HSI) allows for the simultaneous measurement of parameters related to the composition of food products (e.g. moisture content, fat, protein), thus obtaining data in a wider range of spectral bands, which, in addition to providing speed, reliability, and accuracy, reduces human error in the analysis and is non-destructive (Siche et al., 2016). Medus et al. (2021) applied HSI technology to the field of food quality control, which was integrated into the automated control of production lines and capable of detecting up to eleven distinct contaminated products. This application serves to underscore the significance of upholding food safety standards, while also offering novel approaches for the food industry to consistently improve their quality control protocols.

In general, these studies underscore the significant role played by the food industry through the utilisation of advanced technologies and data-driven methodologies. The effective incorporation of emerging technologies not only enhances the efficiency of food production, but also guarantees timely identification and management of potential hazards. In light of the ongoing advancements in technology, it is imperative for stakeholders in the food industry to maintain their dedication towards research, innovation, and collaboration in order to foster the development of a more integrity food system.

3.3. Progressing technologies for food analysis

Food analysis laboratories play a critical role in ensuring the safety, quality, and authenticity of food products. Spectroscopy, chromatography and inductively coupled mass spectrometry and immunological methods are some of the techniques commonly used in food quality analysis. For example, FTIR spectroscopy is a reliable method for detecting suspected food fraud as it allows rapid and simple analysis of various food components such as water, proteins, carbohydrates and lipids (Valand et al., 2020). By this, the potential of FTIR on food adulteration research was demonstrated and deserve further attention. High performance liquid phase chromatography (HPLC) has been widely applied in the lab for analytical research during the past 50 years (Swartz, 2005). Due to the separation characteristic, HPLC is an ideal technique to achieve the detection and measure of component. Khayoon et al. (2010) applied HPLC to achieve the separation and measuring of aflatoxins which are highly toxic compound, and the method is sensitive and reliable to analyse the safety of animal feeds. Mycotoxins are one of the safety risk factors in the food chain and there is a high likelihood of coexistence of multiple mycotoxins in contaminated samples (Rodríguez-Carrasco et al., 2019). One of the state of the art methods in the food sector is UPLC- MS/MS, with the advantages of sensitivity, accuracy and robustness making it a powerful tool for mycotoxin monitoring and dietary exposure assessment (Yang et al., 2022). Furthermore, Droplet digital PCR (ddPCR) is a novel technique for the absolute quantification of target nucleic acid sequences, enabling the detection and quantification of DNA in meat products, which is highly sensitive, specific and accurate for verifying compliance with meat product labelling (Basanisi et al., 2020). To provide a comprehensive overview and facilitate a better understanding of how these techniques are applied across food analysis, Table 2 shows the different targeted laboratory analytical techniques for common food products respectively.

Intelligent technologies have also been applied to testing in recent years, and scholars are interested in improving some testing methods to make them portable and easy to use and are even hoping to use smartphone-like devices for some tests. In response to the current challenges regarding foodborne pathogens, the concept of point-of-care (POC) has been introduced into food testing technologies and devices. POC device development involves technologies such as microfluidics, nanomaterials, biosensors and other advanced technologies, wireless handset-based technologies, lab-on-a-chip and paper-based devices with long-term reagent storage and new test format strategies that offer Low cost, portability and real-time advantages (Neethirajan et al., 2017).

Thus, progressing technologies for laboratory analysis have provided reliable and accurate tools for ensuring food safety and quality. These technologies continue to evolve, providing more effective and efficient techniques for the detection and monitoring of food contaminants and fraud, enabling food producers and consumers to make judgements about food safety and quality.

3.4. Progressing technologies for food chain data

In addition to traditional analytical measurement methods, the growth in the scale of data has given researchers the possibility of building accurate and precise models that can help with decision-making and forecasting in food assurance. Emerging technologies include a wide range of digital tools such as data mobility and big data analytics, blockchain technology, the IoT and cloud computing. These technologies are reshaping the operations of most companies, improving collaboration and facilitating the development of new business models

Table 2
Examples of processing technologies.

Sector	Technology	Concept	Reference
Intelligent Land Technologies	GIS	The use of back propagation neural networks (BP neural networks) to assess land suitability for land planning purposes.	(L. Li, 2011)
		Development of spectral features and feature extraction for land use categories using multi-temporal and multi-spectral (MTMS) Landsat image datasets.	Kumar et al. (2021)
		Remote sensing (RS) is the use of satellite data, such as Landsat and SPOT satellites or ASTER and MODIS instruments, for activities such as biodiversity, nature conservation, food security, deforestation impacts, desertification monitoring, etc.	Blaschke (2010)
	Hyperspectral imaging (HSI)	HSI contains hundreds of adjacent spectral bands provide more detailed results for detecting changes in land cover types and can be used for land use/land cover change prediction analyses. HSI can be carried on various imaging platforms such as satellites, aircrafts, drones, etc. for different inspection purposes.	(Moharram & Sundaram, 2023; Navin & Agilandeeswari, 2020; Seydi & Hasanlou, 2017)
	GPS	GPS devices collect location information to map field boundaries, roads, irrigation systems and crop problem areas, GPS can accurately navigate to specific locations in the field to collect soil samples or monitor crop condition.	Yousefi and Razdari (2015)
	LIDAR	UAV LiDAR offers significant advantages in terms of large and uniform ground coverage in different terrain environments, higher point density and the ability to penetrate vegetation to capture points under the tree canopy.	(Stevens & Johnson, 2016; Yost et al., 2017)
	Wireless sensor network (WSN)	The integration of a wireless sensor network into the proposed soil quality management system allows the measurement of various soil qualities such as conductivity, pH, temperature, NPK (nitrogen, phosphorus and potassium) content and light intensity.	Madhura et al. (2017)
	Geo-referenced environmental monitor	The wireless prototyping system can be used to acquire, store, display and transmit real-time geo-referenced environmental data between multiple field teams and remote locations.	Vivoni and Camilli (2003)
	Weather monitor	The wireless sensor network reports temperature, humidity and sunlight intensity, providing regular information on the weather in the field.	Wang N. et al. (2006)
	Environmental monitor	Wireless sensor networks can include microclimate monitoring of farms and rainforests, water quality soil monitoring and livestock herd monitoring and control.	(Lin et al., 2019; Yousefi & Razdari, 2015)
Intelligent Farm Technologies	Wireless sensor network (WSN)	The intelligent irrigation monitoring system developed using Arduino can be set to a predetermined range of soil moisture and temperature, which can be varied according to soil type or crop type, to create efficient irrigation schemes.	Rajkumar et al. (2017)
		ZigBee technology is used to transmit the information collected by each sensor node, which enables the automatic management of farmland and the accurate measurement and traceability of agricultural products.	(S. Yang et al., 2015)
	Hyperspectral imaging (HSI)	HSI has been widely used in agriculture to collect for different monitoring purposes such as estimation of biomass, nitrogen content, water content, detection of weed classification and crop diseases.	Lu et al. (2020)
	Driverless Technology	Driverless tractors are operated by monitoring sensors and are being developed to operate tractors in a wide range of conditions and practices, such as spraying crop canopies to control insects, diseases and selective weed treatments.	Conesa-Muñoz et al. (2015)
Intelligent Livestock technologies	PLF technologies	Different PLF technologies have been developed to monitor cow production. Sudden changes in animal activity, feeding and watering, body condition and health can be detected by different sensors.	Stygar et al. (2021)
	Autonomous livestock monitoring platform	Automatic image monitoring analysis identifies animal behaviour and movements and performs quick statistics.	Stygar et al. (2021)
	RFID	RFID technology can be used to establish livestock information identification system, which can leave information from breeding to processing, to achieve quality tracking and traceability of agricultural products.	Nikounejad et al. (2022)
	Camera	Smart camera systems using a combination of computer vision and deep learning can monitor feeding times and feed availability at the group level. Camera-based systems have been developed to monitor the drinking behaviour, feeding patterns of livestock.	(Kashiha et al., 2013, 2014; Schillings et al., 2021a; Schillings et al., 2021b)
		In aquaculture, hydroacoustic-based technology and cameras combined with machine learning can monitor pellet consumption and appetite in fish.	Schillings et al. (2021b)
	Sound Analysis	Sound-based systems can be analysed to detect early detection of coughs in livestock that can indicate the onset of respiratory disease.	Carpentier et al. (2018)
	Accelerometer	Accelerometers are mainly used for ruminants and are usually attached to the body of the animal and can monitor the behaviour, position or posture of the individual animal, for example lying, standing or walking.	Schillings et al. (2021b)
Food quality Analysis	IR/NIR	The monitoring of vibrational transitions in IR and NIR allows for the quantitative analysis of the characteristic functional groups of various food components water, protein, carbohydrates and lipids.	Gallo and Ferranti (2016)
	HPLC	The use of chromatographic instruments in combination with a large number of detectors of different properties allows the identification of most of the components of complex mixtures and their quantitative variations and changes in the food matrix.	(Luykx & van Ruth, 2008; Martin & Synge, 1941; X. Wang et al., 2013)
	ICP-MS	MS is used for the analysis of organic molecules, including agricultural and food contaminants such as pesticides, halogenated hydrocarbons, dioxins, and bacterial metabolites in matrices. ICP-MS based techniques allow for the accurate determination of a wide range of elements, such as trace minerals, in order to perform quality assessments.	(Eckhoff & Maage, 1997; Fortunato et al., 2004; Gallo & Ferranti, 2016)

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Table 2 (*continued*)

Sector	Technology	Concept	Reference
	Hyperspectral imaging (HSI)	HSI can detect information related to the physical and chemical characteristics of a large number of food samples and food contact surface materials, so it can be applied in the field of food quality for ingredient quantification.	(Elmasry et al., 2012; H. Huang et al., 2014)
	pH meter	pH testing is essential for food quality because pH affects biological and chemical systems: it influences microbial and spore inactivation, spore germination, the rate of chemical reactions, Murad browning, enzyme activity, protein gel formation and protein denaturation.	(Sadik et al., 2014; M. Zhao et al., 2018)
	Texture profile analysis	Texture profile analysis (TPA) measures and characterises the mechanical properties of food textures by subjecting samples to controlled mechanical forces and analysing their response.	Breene (1975)
	Rheology	Rheology in food quality assesses and understands the flow properties, viscoelastic behaviour and structural characteristics of food materials to ensure desirable textural, stability and organoleptic properties.	(Fischer & Windhab, 2011; Tabilo-Munizaga & Barbosa-Cánovas, 2005)
Food safety Analysis	GC-MS	The coupling of GC and MS allows the detection of endocrine disrupting compounds (EDC), pesticide residues and carbohydrate derivatives thus providing valuable information on the composition and structure of real samples.	(Díaz-Cruz et al., 2003; Ruiz-Matute et al., 2011)
	MS/NMR	MS/NMR based metabolomics is superior to standard methods in modern food analysis and has become the most important technique for the detection and quantification of pathogens, environmental contaminants, banned external compounds and natural toxins.	Castro-Puyana and Herrero (2013)
	PCR	PCR can detect and quantify food allergens and microorganisms and is also used to identify a wide range of foods and to combat food counterfeiting to some extent. In the last few years, several methods based on polymerase chain reaction (PCR) have been proposed as useful tools for identifying species of food origin as well as food allergens and genetically modified organisms (GMO).	Kang (2019)
	ddPCR	Droplet digital PCR (ddPCR) is a novel technique for the absolute quantification of target nucleic acid sequences to detect and quantify DNA in meat products to determine the authenticity of the meat content of meat products.	Basanisi et al. (2020)
	Hyperspectral imaging (HSI)	HSI system is a powerful technology for rapid, non-destructive assessment of the quality and safety of food products affected by the manufacturing process, contaminant detection, defect identification and more.	(Huang et al., 2014; Liu et al., 2017)
	Gel electrophoresis	In food science, gel electrophoresis and advanced electromigration methods such as capillary zone electrophoresis (CZE) and micellar electrokinetic chromatography (MEKC) are used to analyse proteins, phenolic compounds, heterocyclic and biogenic amines, mycotoxins, melamine and melatonin.	Timms and Cramer (2008)
	Genomic/proteomics	Genomic/proteomics methods can be used for analytical purposes to detect the presence of harmful components (e.g., allergens), for sequence-based assays or to provide information on the presence of any pathogenic bacteria or otherwise.	Tewari et al. (2015)
	LC-MS/MS	LC-MS is suitable for the analysis of food contaminants and can provide a wealth of information about complex mixtures, enabling the screening, confirmation and quantification of hundreds of ingredients in a single analysis, checking food authenticity and labelling accuracy.	Malik et al. (2010)
	UPLC–MS/MS	Ultra-performance liquid chromatography tandem mass spectrometry (UPLC-MS/MS) systems have a wide range of applications in the detection of antibiotics, mycotoxins, pesticide residues and metabolomics analysis.	(Iqbal, 2021; Liu et al., 2023; Ly et al., 2020; Yang et al., 2022)
	ELISA	ELISA is a rapid and sensitive method for the detection of harmful microorganisms, pesticide and veterinary drug residues, heavy metals and organic contaminants, and can even determine the levels of different nutrients in food samples.	Wu et al. (2019)
	Lateral flow immunoassay	Lateral flow immunoassay is a stable and cost-effective technique that can be used to detect toxins, infectious pathogens and chemical contaminants in food products.	Raeisossadati et al. (2016)
	NGS	NGS is a developing method combined with bioinformatics to characterise pathogens in food ingredients and products by identifying intact microbial populations.	Jagadeesan et al. (2019)
Sensors & Immunoassay	Intelligent sensor films	Intelligent sensor films can be combined with QR code designs, followed by image analysis and food freshness detection, providing a quality monitor ideally suited to real-time, rapid quality monitoring of large-scale food products, which will ultimately reduce food waste and loss.	Pounds et al. (2022)
	Wireless sensors	Wireless sensors are used in food processing to monitor and control the quality attributes of food products. For example, temperature sensors can be inserted into food tanks to record changes in temperature, and bacteria concentrations in food can also be monitored.	Azfar et al. (2015)
	Nano-sensors	Nanoparticle-based sensors are used to detect a wide range of food-borne bacteria such as E. coli. The use of graphene-based nanomaterials allows for the detection of pesticides by electrochemical and optical methods.	(Bülbül et al., 2015; Y. Li et al., 2019)
	Biosensors	Biosensors are highly efficient analytical devices that have been widely used in the analysis of agricultural and food samples. They can accurately identify heavy metal ions, the misuse and improper application of many pesticides, antibiotics, various pathogenic bacteria and viruses.	(Ashley et al., 2017; Cao et al., 2019)
	ELISA	ELISA sensors are highly sensitive and trace targets can display naked eye detectable colours for pathogen detection and environmental monitoring.	(Lee et al., 2014; C. Zhao et al., 2020)

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Table 2 (*continued*)

Sector	Technology	Concept	Reference
	Lateral flow immunoassay	Lateral flow immunoassay is a cost-effective technique suitable for the detection of toxins, infectious pathogens and chemical contaminants in food, with the advantage of being proven and stable.	Raeisossadati et al. (2016)

designed to increase company profitability. The adoption of digital food assurance solutions can even facilitate the creation of digital ecosystems that enhance coordination between various parts of the supply chain, including external partners, the development of collaborative inter-organisational practices, strategies and processes with these partners, and synchronised production processes (Stevens & Johnson, 2016).

3.4.1. Block chain

One of the modern intelligence technologies, blockchain, which is an innovation in decentralised information technology, suggested an entirely new strategy (Tian, 2017). The utilisation of blockchain technology has witnessed a notable rise in the realm of intelligent food systems, signifying its emergence as a prominent technological innovation in recent years. The system may contain an infinite number of blocks, each of which contains chronologically ordered information about all transactions that have occurred over a specific time period. The blockchain stores data that is accessible to the public and is a nearly immutable record of the network's history. This data is shared by all nodes in the distributed network, ensuring the security and integrity of the information along the chain between system nodes (Monrat et al., 2019).

Galvez et al. (2018) investigated the potential of blockchain technology to guarantee traceability and authenticity in the food supply chain. By comparing this approach with current food supply chain management systems, it was concluded that the proposed technology is more efficient and secure in solving the current problems in the food supply chain industry. Meanwhile, a study by Vincent et al. (2020) suggested that implementing a blockchain approach could bring benefits to the food supply chain industry such as improved security and a more dynamic and flexible organisation, but that the costs of implementing the approach would outweigh the benefits. On the other hand, there are still a few barriers and challenges to smart technologies in food supply chain management, such as the emerging discussion on how digitalisation may exacerbate power inequalities in the food system, as it can become over-controlling when transparency facilitates the proliferation of audit, evaluation and assessment measures (Vistro et al., 2021).

Based on the above research, the following Fig. 5 can be briefly summarised as a model for the operation of a blockchain-based food system. The periphery icons in the diagram below shows the linear flow of information in the supply chain in a chronological order, which corresponds exactly to the linear upload of information between blocks in a blockchain. As the information in the blockchain is immutable, there will be fewer information gaps between further parts of the supply chain, largely ensuring the integrity and transparency of the food chain.

3.4.2. Data science

The volume of data generated by all sectors of the food chain continues to grow, providing opportunities to improve decision-making and product quality through data analysis. Data science, which involves the use of automated methods to extract knowledge from large volumes of data, is a rapidly growing field that includes a number of disciplines such as mathematics, statistics and machine learning. In spite of its relatively recent emergence, existing theories emphasise the analytical and processing capabilities of data science, which can assist in decision-making and forecasting in the food assurance field. The system developed by Lao et al. (2012) was an example of an integrated prototype that can help companies with inventory management and minimise potential threats in storage. Liu et al. (2020) used big data and blockchain technology to propose a suitable supply chain structure. There are still knowledge gaps regarding the unique opportunities and challenges associated with big data in food safety (Jin et al., 2020). These studies shed light on the potential of big data for food safety, but also highlighted the need for further research and exploration of the topic.

Despite the success of data science approaches in various food-related fields, there are still knowledge gaps regarding the unique opportunities and challenges of big data and its use in decision-making. However, data science techniques provide a powerful knowledge management tool for data mining and processing in intelligent food quality assurance systems and can help managers to harness the vast amount of data available within the supply chain.

3.4.3. Machine learning and artificial intelligence

The fields of Machine Learning (ML) and Artificial Intelligence (AI) have grown and developed significantly in recent years, affecting almost every aspect of modern society. This progress has been made possible by the availability of digital data, computing power and advanced

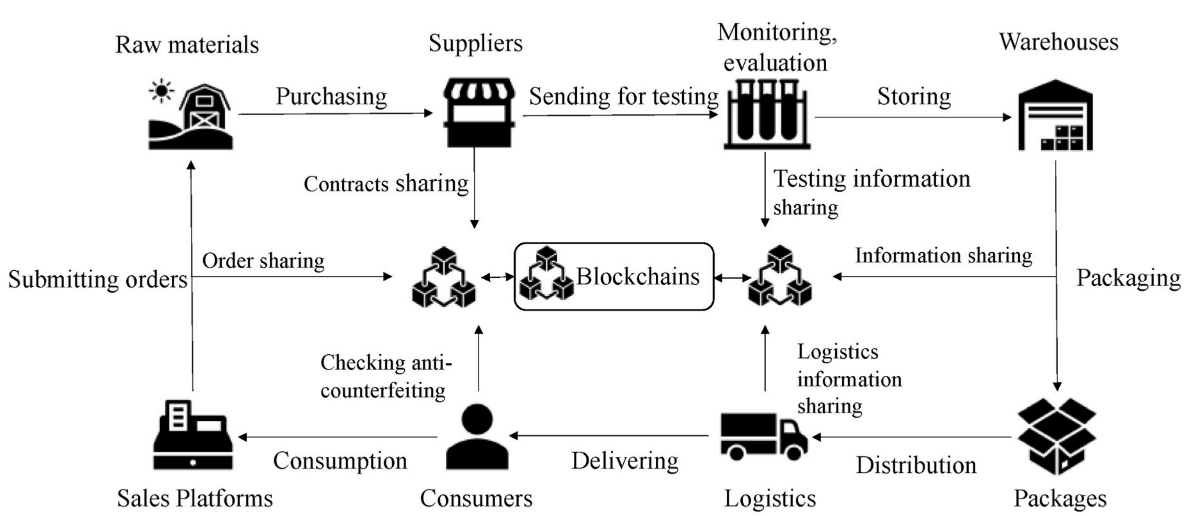

Fig. 5. Blockchain processes in the food chain.

algorithms applied to ML and AI systems. The history of ML involves attempts to create artificial neural networks that mimic the neural connections and information processing of the human brain. These networks use complex mathematical frameworks to model the non-linear relationships between input and output data. Food quality and safety issues can arise at any point in the food supply chain, so it is vital to develop systematic ways to identify potential risks. ML and AI techniques have the potential to improve the accuracy of risk identification and prediction by learning from previous experiences and cases. Recent research has demonstrated the effectiveness of these technologies in addressing a variety of food-related challenges. For example, Kong et al. (2021) developed a deep stacking network to identify hidden risks in food supply chain management using large amounts of data obtained from the internet. Liu (2016) proposed a system to improve the accuracy of diet assessment by analysing food images taken by mobile devices, while Song et al. (2017) used a deep denoising auto encoder to predict the effect of food contamination on gastrointestinal infections. For fruit cold chain logistics, machine learning-based prediction methods are non-destructive, far easier to operate than traditional prediction methods, and can even improve in-process freshness prediction accuracy and food quality management (Huang, Wang, Zhang, et al., 2023). These and other ML and AI approaches show great promise for improving food safety and quality. In addition to identification, monitoring and prediction functions, there are other applications of AI in the agri-food industry. Di Vaio et al. (2021) examined the role of stakeholders in the agri-food supply chain and the potential of AI to improve productivity, reduce waste and enhance sustainability. Kakani et al. (2020) explored the latest AI and computer vision technologies that can help farmers in agriculture and food processing. Zhu et al. (2021) provided an overview of traditional ML and deep learning approaches, as well as machine vision techniques that can be applied in food processing. These studies seem to imply that ML and AI are transforming the agri-food industry, providing new solutions to food safety, quality and sustainability challenges. As the field continues to evolve, the importance of these technologies in food assurance is likely to grow every day.

4. Current status of intelligent food assurance systems

The use of intelligent technology is becoming increasingly common in the food industry. Systems have been developed using a combination of a range of technologies to monitor, track and control all aspects of the food supply chain in real time as the origins of an IFAS. The following sections provide an overview of the status of selected key technologies that can be used in the broader remit of an IFAS.

4.1. Intelligent labelling, packaging and traceability systems

Intelligent labelling and packaging technologies have been developed to enhance the safety and quality of food products. Packaging systems maintain the quality of the product over time and also help to reduce waste. The main factors that determine the quality, safety and shelf life of food products include temperature, oxygen concentration, carbon dioxide concentration, relative humidity and moisture content as well as product properties (Pereira de Abreu et al., 2012). These technologies include indicators that change colour when a product is nearing its expiry date, temperature sensors that detect temperature variations during storage and transportation, and intelligent packaging that can detect and alert to product spoilage or contamination. Intelligent labelling and packaging can also provide consumers with information about the origin of the food, the production process, and the presence of allergens, making it easier for consumers to make informed decisions about the food they purchase (Yam et al., 2005). Food traceability is the ability to track and trace food products as they move through the supply chain, from farm to fork. This approach is becoming increasingly important for improving food safety, reducing food waste, and improving sustainability in the food industry. Ensuring food safety is the fundamental driver and need for the food industry, Rahmat et al. (2016) found through the identification of public and private food safety and quality standards internationally, and the implementation of food quality standards in three different regions, that given the concern for food quality assurance and improved consumer confidence, many companies have developed a traceability system to visualise the supply chain and avoid food safety incidents. Traceability systems can help identify where and when a product was produced, processed, and transported, making it easier to track down the source of fraudulent activities (Aung & Chang, 2014). In recent years, there has been a growing interest in using advanced technologies such as blockchain, RFID, and QR codes to enable more effective food traceability. Alfian et al. (2020) incorporated machine learning models into RFID gates so that tagged products entering and vacating the gates could be accurately identified, thereby enhancing the efficiency of the traceability system. Digital information systems can advantageously contribute to traceability, and blockchain technology allows for the integrity of the food chain by storing data irreversibly (Galvez et al., 2018; Tian, 2017). It is apparent that advances in smart labelling and packaging technology are revolutionising the food industry, ensuring safer and better-quality products, while promoting transparency and informed decision-making. These innovations, coupled with a growing focus on traceability and the integration of advanced technologies, are reshaping the food system landscape.

4.2. Intelligent sustainable systems

In recent years, the focus of food systems has shifted from traditional supply chain management to sustainable food supply chain management. Intelligent food sustainable systems refer to advanced technological solutions that employ data-driven approaches to create a sustainable and efficient food production system. Artificial intelligence and digitalisation show great potential to support the transition to sustainable food systems (Marvin et al., 2022). Various researchers have explored different aspects of sustainable food supply chain management, from identifying key logistics objectives to proposing models of surplus food generation and management. Kong et al. (2021) proposed a deep stacking network optimised by data mining to improve the efficiency and performance of RITS to ensure the sustainability of food supply chain safety. The valorisation of food waste in the supply chain can be transformed into biofertilizer, animal feed, platform chemicals, bioelectricity, animal feed etc. through biological processes. Smart technologies can be combined with sustainable value addition for the selection of potentially high value FW, quality identification, odour-based sorting, supply chain management, and final disposal (Said et al., 2023). Intelligent technologies can also help to reduce packaging costs and food processing, storage and transport can all benefit from them, such as robots and smart drones (Grác et al., 2020). In combination with the aforementioned precision farming systems, intelligent computing and decision-making can be used to maximise the use of resources and increase food production wherever possible. However, a structured analysis of the commonalities between these studies is lacking, which could improve clarity and efficiency in assessing and managing the collaborative performance of sustainable agri-food supply chains. It is evident that smart technologies show great potential to support the transition of food chains to sustainable food systems.

4.3. Intelligent monitoring and control systems

The development of intelligent monitoring and control systems for the food industry has been an area of active research in recent years. Li et al. (2006) proposed a dynamic planning approach for agri-food supply chains that aims to minimise losses while maximizing profits for all members of the supply chain. Lao et al. developed the Intelligent Food Quality Assurance System (IFQAS), which automates decision-making processes for food storage quality control (Lao et al., 2012). Yan-e

(2011) presented a case study of CPNS intelligence to prevent foodborne disease outbreaks. Chen (2017) proposed a novel value stream-based approach to food traceability, which integrates enterprise architecture, EPC global, and value stream mapping to achieve collaborative efficiency in traceability through a fog computing network. Recent research has focused on the application of intelligent technologies to food safety, such as the proposal of a decentralised traceability system based on HACCP with the IoT and blockchain technology, which provides real-time food safety information to various members of the supply chain, enhancing security, transparency, and collaboration while improving the efficiency and transparency of the food supply chain (Tian, 2018). This system offers real-time safety information to all supply chain participants, thereby bolstering security and enhancing collaborative efficiency. Furthermore, IoT technology's role in collecting critical quality-related data in food service environments has been advanced, such as the use of Bayesian modelling techniques on the Fog-Cloud platform for analysing food data to generate consistent probabilistic indicators of food grade (PoFGs) (Bhatia & Manocha, 2022). Huang, Wang, Xia, et al. (2023) discussed the effective combination of emerging flexible sensing technologies with smart devices and intelligent algorithms for high-precision sensing, multi-scale monitoring and non-destructive testing of agricultural product quality in the cold chain, and that this intelligent, miniaturised, multi-scale technology was an important future direction for agricultural technology. These studies demonstrated that the systematic application of smart technologies for food safety, quality control and traceability is progressing rapidly and has great potential to improve efficiency and transparency in the food industry. However, the most existing research focuses on a single purpose, and existing models tend to intelligently analyse and process the same type of information. This means that there may be opportunities in the food industry for a system that can process multiple formats of information, or a system that can aggregate multiple models.

5. Discussion and future trends

5.1. Benefits and limitations of intelligent food systems

5.1.1. Benefits

Building upon the insights gathered in the previous sections, the potential benefits of integrating digital technologies in IFAS can be identified. The benefits in the field of agriculture are mainly in the areas of production monitoring and resource utilisation efficiency, which may be beneficial in terms of reducing resource wastage and sustainable development. The progressing food analytical technology has clear qualities to ensure food quality and safety, and when combined with existing risk systems can have the potential to ensure food authenticity and food defence. Intelligent food systems are characterised by the integration of advanced technologies such as artificial intelligence, the Internet of Things (IoT) and big data analytics, which have the advantage of being quick to respond, helpful in decision-making, and allowing knowledge to be gained from previous experiences. In summary the potential benefits of IFAS can be summarised in the following 4 main points:

Food assurance: Among the key benefits of IFAS can be the ability to detect and prevent food inauthenticity, contamination and other safety issues in real time. By using data analytics, machine learning and artificial intelligence, these systems can analyse large amounts of data to enable early detection of safety issues and fraud attempts. At the same time, concerns about food safety and risks associated with food consumption are key factors in consumers' decisions, but they may have difficulty assessing food risks on their own, so they must rely on the expertise and information provided by retailers, manufacturers or health authorities (Liana et al., 2010). IFAS will selectively make key food data transparent due to its control of supply chain data, making it easy for consumers to monitor the quality and safety of food.

Food transparency: An easy-to-understand information system that brings more transparency and builds consumer trust, thus the future research on Internet of Food seems promising for the food industry and is seen to bring about a paradigm shift in the farm-to-table approach (Kodan et al., 2020). This increased transparency and traceability can increase consumer trust and confidence in food and provide valuable information to regulators and other stakeholders. In addition, the implementation of IFAS will increase transparency and traceability in the supply chain, as the system is proposed to involve information from stakeholders across the supply chain. Through the use of smart sensors, blockchain technology and other tools, food can be monitored from farm to fork, providing detailed information on each link in the supply chain.

Food waste and sustainability: In addition to the aforementioned benefits demonstrated by precision agriculture, digital technologies such as IoT are likewise playing a role in the area of sustainability. Jagtap et al. (2021) proposed an IoT-based framework for monitoring food waste generation as well as energy and water use in the food industry in order to optimise the resource efficiency of food manufacturing, leading to significant environmental and economic benefits. Sharma et al. (2020) argued that blockchain technology could significantly benefit the creation of greener IoT ecosystems, potentially helping to reduce the greenhouse effect and fostering sustainable ecosystems by optimising energy use and increasing bandwidth utilisation.

Business value: Implementing an IFAS can also help businesses cope with risk in an unpredictable economic environment. Early detection not only helps to protect consumers, but also minimises the risk of product recalls, lost revenue and damage to brand reputation. For businesses, as well as increased efficiency which will be the main benefit, IFAS can serve as a marketing strategy to increase consumer trust and enhance core competencies. Another benefit of IFAS is their ability to optimise production processes, reduce waste and increase productivity. Park and Li (2021) demonstrated through a literature review and case studies that blockchain technology has the potential to improve supply chain sustainability performance. By using real-time data, these systems can identify inefficiencies and areas for improvement, enabling companies to make data-driven decisions about their operations, which can lead to cost savings, improved resource utilisation and productivity.

5.1.2. Limitations

While the application of these technologies signals the advancement of Food Industry 4.0, the constraints and challenges that accompany these advances are viewed from a balanced perspective. The benefits drive the realisation of a more efficient and safer food supply chain, and the limitations serve as a reminder of the practical challenges and ethical considerations inherent in the integration of such technologies.

Technical Challenges and Cost Implications: The costs associated with intelligent upgrades to food systems that may hinder their widespread acceptance include set-up or capital costs, running or operational costs, and upgrade costs, which also implies a need for relevant technical expertise (Chamara et al., 2022). Developing and implementing intelligent systems may have costs in terms of technology, hardware and skills training. As a result, the small size and low-cost operations of some companies may exclude digital transformation. It does not mean that there are no opportunities for digital transformation in some businesses, but rather that the development of such products could take into account the need for low cost and ease of operation.

Data Privacy and Security Concerns: Data privacy and security issues may also pose challenges to the implementation of IFAS. The collection and sharing of data between different stakeholders can be complex and requires careful consideration of privacy and security implications. The food supply chain also lacks a strong cyber insurance policy, and the various cyber risks involved are difficult to predict and quantify (Gupta et al., 2020). Strong data protection protocols and procedures must be in place to ensure that sensitive information is secure and that the privacy of consumers and other stakeholders is protected.

Potential for Disparities: Different regions of the world currently may have various food assurance standards. Because of national and religious differences, government attitudes and systems will be the restraining force in the development of various food systems (Lei et al., 2022). There is already an eagerness to establish cooperations between different regions, for example Qian et al. (2020) argued that a common food system in Central Europe needs to become a modern risk communication mechanism to enhance communication between scientists, risk assessors, risk managers and consumers. The development and implementation of these systems must be carefully considered and planned to ensure that they are effective, efficient and protect the interests of all stakeholders involved in the food supply chain.

Actual financial benefits: While the literature and case studies suggested that supply chain sustainability performance could benefit from blockchain technology, it is worth noting that there is still a lack of estimated correlations and causal inferences identified between the adoption of digital technology-based supply chains and sustainability performance (Park & Li, 2021). Therefore, there are limitations to the impact that smart food systems may have on direct financial benefits.

In summary, future trends in intelligent food system design will focus on how to capitalise on the aforementioned strengths and current limitations of customer service. These trends show that technology can not only improve food safety and quality, but also drive innovation and sustainability. It also provides basic ideas for the design of an IFAS, where digital technologies bring benefits to the food system while at the same time focusing on the problems they have, so that an IFAS will be a robust digital solution.

5.2. Design challenges for IFAS

The challenges faced by IFAS are mainly in three areas: regulation, technology, and application. The successful implementation of IFAS may require integration with existing food safety management systems such as HACCP, VACCP and TACCP, which requires collaboration between different stakeholders and the development of standardised protocols and procedures. Such integration constitutes one of the main challenges in implementing an IFAS, which requires not only the categorisation of different forms of data, but also the rationalisation of how different food risks are handled and prioritised in the system. In addition to the FFVA described above, which can be used as the underlying design rules for a food risk system, Asselt et al. (2018) used decision trees to construct a transparent and proven risk-ranking methodology for classifying chemical substances, which was used as a tool for developing risk-based monitoring programmes.

It is difficult to integrate and make use of the vast volumes of data involved in the food chain, which come in many various formats. There are already intelligent models that can respond to specific food problems, which from a machine learning perspective means that there are many different designs of decision trees. Each decision tree only needs to process one type of information and output the result, and when the models that separately cope with different problems of food are combined together, the IFAS as a decision forest for food problems is obtained.

At the application level, the cost and complexity of implementing IFAS can be prohibitive for small and medium-sized enterprises (SMEs).

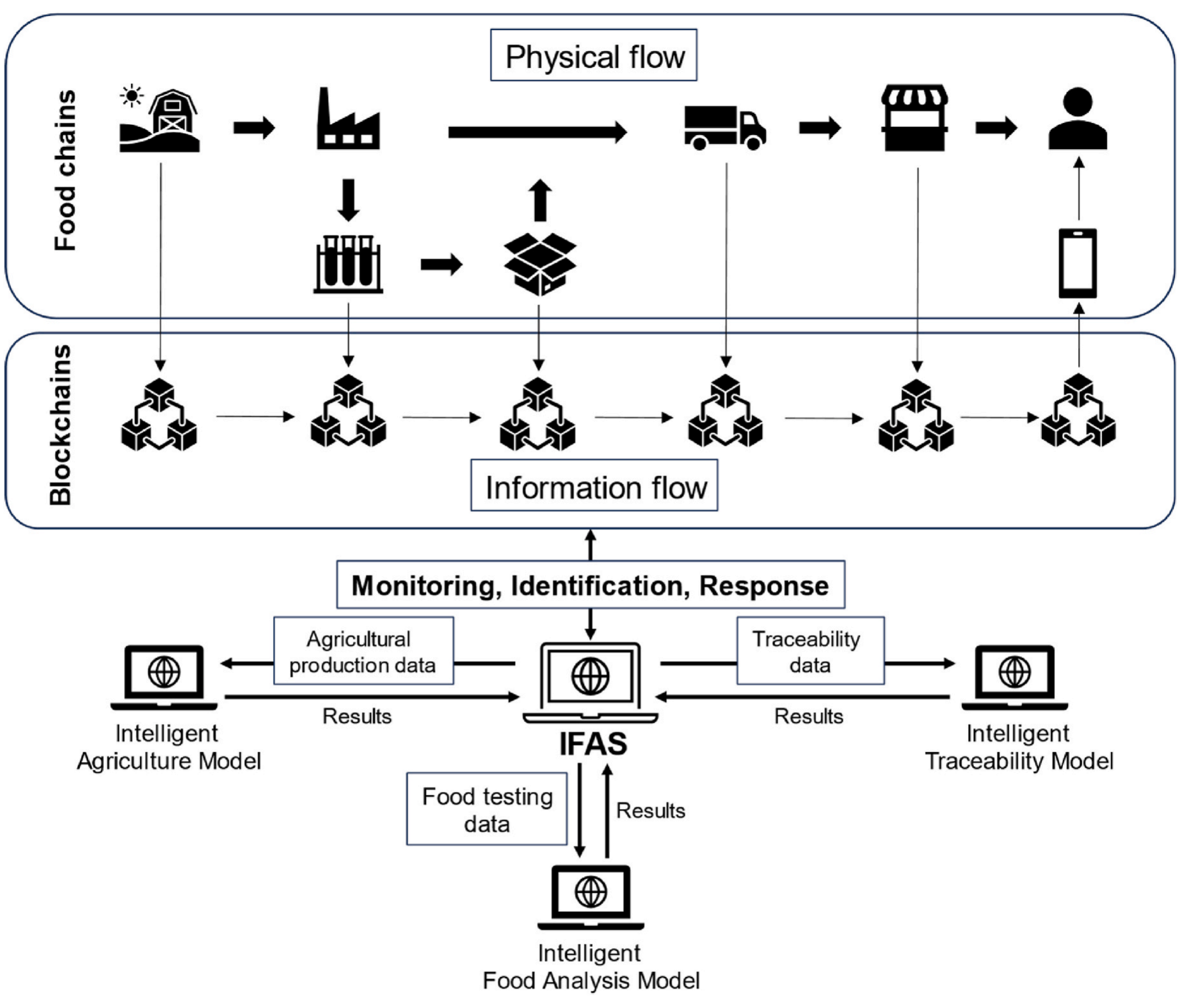

Fig. 6. The flow of IFAS.

User resistance due to a lack of understanding or trust in the technology can also be a significant barrier. Future research may look for cost-effective, scalable IFAS solutions that can be used by organisations of all sizes, with technical training and user-friendly interfaces helping to increase acceptance and adoption of IFAS.

Fig. 6 illustrates the operational flow of the proposed IFAS and shows in detail the flow of information with the supply chain and the processing. More detailed establishment and operation of IFAS will be explored in future studies, and there may be potential for specific business practices. As can be seen through this flowchart, the utilisation of the IFAS system to improve the efficiency of communication and sharing to ensure uniform standards in the food chain will probably be another key to the implementation of food assurance by IFAS.

5.3. Future trends

The development and application of digital systems for the food industry is a continuous process. While there are challenges, the potential benefits are significant continued research and investment in this field. In this section, we discuss some of the potential future research directions that could further improve the efficacy and adoption of intelligent food assurance systems.

From a production perspective, robotics and automation are one of the main drivers of Industry 4.0 and one of the future trends in the development of smart food systems, e.g. the development of specific effectors for food processing robotics (Hassoun et al., 2023). Production requirements and standards are different for various agricultural products, so it may be necessary to target research and practice towards subsectors such as dairy, meat and farming. For research to establish similar systems, it is important to consider not only the utilisation of the advantages of digital technology, but also ways of dealing with potential issues.

At the same time, for the discipline of Information Technology, there are some gaps in the research about intelligent food system modelling, such as multi-model integration and practical examples. The DevOps approach as an integrated system building model with multi-team collaboration will be the next step of this study. Interdisciplinary collaboration and research will be the future focus of such studies. For research in anticipation of food technology, the development of low-cost, easy-to-operate citizen solutions is a rarely explored direction, especially portable processing solutions that can penetrate the market. The security and privacy of intelligent systems is not only a challenge for digitisation in the food industry, but also an opportunity for future research. Future trends may include the development of stronger cybersecurity measures to protect sensitive consumer and business data.

Also, from a business and market perspective, as well as focusing on the economic benefits of sustainability, it is important to consider correlation studies between intelligent systems and direct financial benefits. The promotion of such systems could also take into account individual customisation for different volumes of supply chains, as well as skills training, system maintenance and other services.

As environmental issues become more pressing, intelligent food systems are likely to place greater emphasis on sustainability. This may include optimising resource use, reducing food waste through better supply chain management and implementing sustainable practices in food production and distribution.

Future research in food systems will continue to focus on basic food assurance and sustainability, and exploring the added value of food systems will be a long-term endeavour. These trends suggest a vibrant future for the smart technology enabled food industry, with future research emphasizing that the benefits of these systems can be widely realised across the food industry.

6. Conclusion

This review has explored the current landscape of an IFAS and their potential to improve food safety and authenticity. Through an examination of emerging technologies in the food supply chain, as well as current applications of precision farming and an IFAS, we have identified several key opportunities for improving the efficiency and effectiveness of food assurance systems. These opportunities include the introduction of automation technologies, the transfer of business value, and the development of standardised protocols for collaboration. Despite the many promising developments in this field, several challenges and limitations remain. These include the need for greater data interoperability, improved regulatory frameworks to support the adoption of intelligent technologies, and increased public awareness and trust in these systems. Additionally, it will be important to address potential ethical concerns around the use of intelligent technologies in the food supply chain, such as data privacy and algorithmic bias. Looking to the future, we envision a more robust and integrated food assurance system that combines the strengths of multiple technologies and approaches. This system would be built on a foundation of standardized protocols and metrics, with data from across the food supply chain collected and analysed in real-time using advanced analytics and machine learning. At the same time, IFAS would be designed with flexibility and scalability in mind, allowing it to adapt to changing needs and circumstances.

The goal of an IFAS would be to provide a more efficient and reliable means of ensuring the integrity of the food supply chain. An IFAS aspires to accomplish the right response in the right location at the right time in the future management of food operations by leveraging intelligent technologies. Achieving this vision will require sustained investment in research and development and cooperation at all ends of the food chain. Modern agriculture and the food industry need to keep pace with technological advances and maximise their benefits.

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Declaration of competing interest

The authors have nothing to declare for this manuscript.

Data availability

No data was used for the research described in the article.

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