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Industry 4.0 technologies in quality and safety control systems in food manufacturing: A systematic techno-managerial analysis on benefits and barriers

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A B S T R A C T

Background: The food industry faces increasing demands for improved quality and safety, while conventional quality control methods remain labour-intensive, slow, and limited. Industry 4.0 (I4.0) technologies show promise, but real-world implementation remains limited. Advancing practice requires clear insight into technical/technological and managerial benefits and barriers.

Scope: This review examines the I4.0 technologies and their implementation status in quality and safety systems in food manufacturing, and their applicability in either product or process quality control, as well as in elements of the quality control circle (data collection and analysis, corrective and proactive actions). Followingly, the benefits and barriers of these technologies that are mentioned in the reviewed studies are categorised using a techno-managerial approach.

Key findings and conclusions: Artificial intelligence (AI) is mainly used for product quality control, while the Internet of Things supports process quality control in the reviewed studies. Data analysis is the most addressed element of the quality circle; AI has the most potential. The reported benefits are primarily technical/technological, focusing on contamination detection and real-time quality monitoring. Managerial benefits, though less emphasised, include cost-effectiveness, better food safety and crisis management, and strategic improvement. Key technical/technological barriers are *process and equipment-related*, notably the need for high-quality data and time-intensive AI model training for large or complex datasets. Besides, reliable and accurate performance can still be a barrier due to overfitting, misclassification, etc. Managerial barriers are mostly *people-related*, including manual labelling errors and security issues. A multidisciplinary approach is essential to overcoming these barriers and promoting field implementations.

1. Introduction

In the last decades, consumer and customer interest and demand for better food quality, safety (Hassoun et al., 2023a), authenticity, traceability, and sustainability (Henrichs et al., 2022) have created a competitive food industry ambient. Additionally, the COVID-19 pandemic has presented new challenges for competent authorities and food professionals in terms of routine inspection, control, monitoring, and surveillance of food quality and safety parameters, as well as sampling and analysis of food, and managing food incidents (FAO/WHO, 2020). Although conventional food quality and safety control methods are useful, they often suffer from having a laborious and destructive nature, high cost, long processing time, limited number of analytes, low performance, limited test scope, lack of sensitivity for detecting low levels of contaminants or adulterants in food, etc. (Hassoun et al., 2023a; Djekić et al., 2023). The reshaped demands, experienced challenges, and current drawbacks of conventional methods have been driving the food industry and researchers to seek more innovative ways and technological solutions for food quality and safety control, leading to increasing awareness and interest in adopting digital technologies (Hassoun et al., 2023 a,b). According to Djekić et al. (2023), conventional food quality and safety control practices can be improved and complemented with advanced digital technologies, such as predictive analytics (i.e., forecasting outcomes based on historical and current data), prescriptive analytics (i.e., recommending best actions or solutions based on data analysis and business rules), cognitive analytics (i.e., understanding and

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interacting with human speech, images, and sounds), and edge computing (i.e., using edge devices to process data locally, reducing latency, bandwidth, and storage costs).

The potential of digital technologies in food quality and safety control is widely recognised by official organisations. FAO's 2023 strategic priorities (2022–2031) for food safety emphasise the need for digitalisation and technological modernisation in food control. Similarly, World Health Organization (WHO) (2022) highlights digital transformation as a key driver shaping the future of food safety. The European Commission (2021) projects that over 90 % of European SMEs will achieve at least basic digital intensity by 2030.

With this growing interest and acknowledgement in the adoption of digital technologies in food quality and safety control, many researchers have focused on the application and impacts of Industry 4.0 (I4.0) technologies (such as artificial intelligence (AI), big data, the cloud, the Internet of Things (IoT), blockchain, digital twins, 3-D printings etc. (Hassoun et al., 2023a-b; Djekić et al., 2023; Bai et al., 2020). For instance, Chatterjee et al. (2024) examined the impact of I4.0 technologies on food and beverage companies in India, while Romanello and Veglio (2022) investigated the drivers, challenges, and outcomes of I4.0 adoption in an Italian food processing firm. On a broader scale, Konfo et al. (2023) addressed challenges and opportunities for the adoption of these technologies in the agri-food sector. Senturk et al. (2023) discussed the potential advantages and disadvantages of specifically IoT and related technologies in agricultural practices. Similarly, Kaur et al. (2022) explored the potential of blockchain and IoT technologies in the food supply chain. Sustainability has also emerged as a theme in this topic. Sharma et al. (2023) assessed critical barriers to implementing digital technologies in food supply chains for sustainable production and consumption, while Hassoun et al. (2022) examined their role in accelerating the global transition towards sustainable food systems. Adding to this, Hassoun et al. (2023b) discussed how I4.0 technologies and advancements can support the food industry, highlighting the overlooked human factors in their implementation. Trevisan & Formentini (2024) assessed the adoption of these technologies in the agri-food supply chain, emphasising their potential to prevent and reduce food loss and waste throughout the supply chain. Together, all these studies underscore the growing interest in I4.0's role in the food sector.

The concept of I4.0 has extended to food quality, forming "Food Quality 4.0" (FQ4.0), which focuses on determining food quality efficiently using digital technologies (Hassoun et al., 2023a). In their study, Hassoun et al. (2023a) discussed a selection of the most commonly used non-destructive and non-targeted fingerprinting methods, such as spectroscopic and imaging techniques, within the context of FQ4.0, highlighting the promising role of AI and big data in enhancing food quality and safety. They also noted uncertainties about broader adoption and called for more systematic reviews. Djekić et al. (2023) describe the FQ4.0 concept as using I4.0 technologies and data analytics to automate and optimise quality management. In their study, they explain its evolution from Food Quality 1.0, comparing it with traditional food quality by considering products, processes, systems, and sustainable (nano) technologies for enhancing manufacturing and waste reduction. While these studies offer foundational insights regarding the FQ4.0 concept from a broad perspective, systematic research is still needed on the benefits of I4.0 technologies in quality and safety control systems.

Despite their potential benefits, various barriers may hinder the adoption of these technologies, such as accessibility, management of data, security, lack of finance, technological awareness, and knowledge and skills (Jagatheesaperumal et al., 2021; Romanello and Veglio, 2022). However, these barriers are general and not specific to food quality and safety control. Implementing I4.0 technologies into food quality and safety control can bring not only technical aspects but also impact organisational structure and culture, requiring a multidisciplinary approach that addresses both technical and managerial aspects, as advocated by Luning and Marcelis (2006, 2009).

This paper presents the applications, benefits and barriers of I4.0 technologies for food quality and safety control systems in the food manufacturing stage based on a multidisciplinary techno-managerial (T-M) approach applying a systematic literature review. The review covers product and process control systems involving data collection, data analysis, and corrective/proactive actions during production.

2. Systematic literature review approach and thematic analysis

2.1. Review protocol

In this study, a systematic literature review methodology (Fig. 1) was conducted since it can provide a structured, comprehensive and transparent assessment of the available knowledge from the scientific literature (Biesbroek et al., 2013). As shown in Fig. 1, firstly, core concepts (i.e., digital; food; quality; control) and their synonyms were identified (for details, see Table S1) to be able to reach the relevant knowledge for the defined research aim. Following that, an explorative literature assessment was performed through certain databases to determine the keywords that were connected to core concepts, and the inclusion and exclusion criteria.

As the inclusion criteria, English review and research articles (2017–2024) from peer-reviewed journals focusing on I4.0 technologies in food quality and safety control systems at the manufacturing stage were established. Review articles were used for snowballing to check any other relevant research articles and information. Articles that discuss the agricultural, farming and supply chain stages other than manufacturing and focus on plant or human treatment were excluded. Based on the defined criteria, search strings were designed with Boolean operators (Table S2) and used in the corresponding databases.

2.2. Extraction of data

The collected research articles were examined for the extraction of

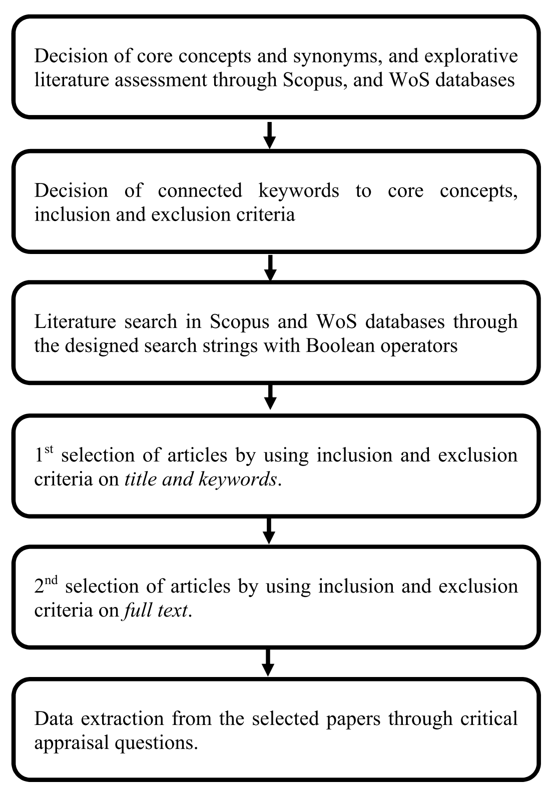

Fig. 1. Systematic literature review protocol (adapted from Biesbroek et al., 2013).

relevant data through the designed critical appraisal questions (Table S3). These questions provided a systematic and transparent reviewing process of the information given in the articles in three main aspects; (i) the name, aim of developed technology and principle, implementation status (i.e., lab-tested or field-tested), applicable quality control type (i.e., process or product) and quality control circle elements (i.e., data collection, data analysis, corrective actions and proactive actions), and (ii) the benefits and (iii) barriers from the technological and managerial perspectives. In the current study, the technological perspective covers food production processes with typical product features, process and equipment, and production environment aspects (Luning and Marcelis, 2020) and technical aspects of technologies relating to the knowledge, machines, or methods (Cambridge Dictionary, n.d.); the managerial perspective involves people, organisational structures and procedures aspects (Luning and Marcelis, 2020).

2.3. Analysis of qualitative data on benefits and barriers: A thematic analysis using a techno-managerial approach

A qualitative analysis of identified technical/technological and managerial benefits and barriers was performed through a thematic analysis to identify themes from the data/information from the literature. As the first step of the thematic analysis, the collected useful texts on benefits and barriers were re-read to get familiarised with the data. Subsequently, the units of analysis were decided for each useful text part per article. As the third step, the context units (i.e., full phrase or paragraph that assigns the meaning to the unit of analysis) were extracted from the collected useful texts. In the next step, similar or relevant context units were grouped, and an overall name (theme) was assigned for each group (e.g., "non-destructive quality control" or "high-quality data and time requirements"), which is called the 'core of meaning' (Zanin et al., 2021; Almansouri et al., 2022). Each assigned core of meaning corresponds to a sub-category. Subsequently, the barriers were further categorised into broader main technical/technological and managerial categories as described in section 2.2. This further classification of barriers facilitated a systematic approach to addressing them.

3. Industry 4.0 technologies for food quality and safety control systems

Various studies reviewed the applications or suggestions for the use of I4.0 technologies in agriculture (Cricelli et al., 2024; Yadav et al., 2022) or food supply chains (Hamill et al., 2024; Malik et al., 2024; Shiraishi et al., 2024). However, the current study focuses on their applications in the quality and safety control systems in the food manufacturing stage. In total, 38 research papers were found relevant based on the defined criteria and systematically analysed. Table 1 presents the identified I4.0 technologies and their combinations with other tools, their implementation status, their applicability in product/process quality control, and quality control circle elements. Two implementation statuses were considered: *laboratory-tested*, referring to tests under controlled scientific conditions in a laboratory or similar setting (Merriam-Webster, n.d.), and *field-tested*, referring to tests in actual situations reflecting intended use (Merriam-Webster, n.d.), either in place or with collected data from the field. Besides, *product* and *process quality controls* refer to measuring product properties, including safety, and measuring process parameters that affect product quality (Luning and Marcelis, 2007). Additionally, the *data collection* element of the quality control circle means measuring the product properties and process parameters; the *data analysis* element involves comparing the measuring outcomes against the established norms and limits. The element of *corrective actions* encompasses the process of assessing deviations from the norm, determining appropriate interventions, and implementing corrective measures (Luning and Marcelis, 2020), and *proactive actions* involve feedforward quality control, focusing on prevention, early

Table 1
Industry 4.0 technologies with the type of quality control they applied and their aim; quality control circle elements in which those technologies can perform.

Technology*	Type of quality control and aim of the design	Application of technology in Quality Control Circle[#]
Artificial Intelligence – Implementation status: Laboratory-tested		
Neural networks (Chenchouni and Laallam, 2024)	**Product (honey) quality control:** The design aims to reveal the combined impact of various factors (i.e., climate zones, honeybee breeds, honey extraction methods, and beekeeping systems) on honey quality.	• DA via NN algorithms.
Optical emission spectrum-based instrument (μPD-OES) combined with ML (Ren et al., 2024)	**Product (meat and coffee) quality control:** The design aims to facilitate on-site evaluation of food freshness and adulteration detection.	• DC via a designed portable device • DA via ML • CA and PA via assessment of meat quality and discrimination of possible food fraud
Combination of a digital camera with ML (i.e., convolutional neural network) (Przybył et al., 2023)	**Product (roasted coffee) quality control**: The design aims to identify the quality classes of Arabica coffee beans based on the roasting process.	• DC via camera • DA via CNN
Combination of chromatographic fingerprinting with AI (Squara et al., 2023)	**Product (hazelnut) quality control:** The design aims for an accurate and multi-target quantification method which targets quality markers of raw hazelnuts.	• DA via AI-smelling machine • PA via decision-makers for rancidity level and storage quality; origin tracers
ML-assisted Raman spectroscopy (Zhang et al., 2023)	**Product quality (i.e., microbiological) control;** the design is proposed for real-time detection of a panel of foodborne pathogen-specific molecular fingerprint volatile organic compounds.	• DC via developed portable Raman probe to collect fingerprint VOCs of foodborne pathogens • DA via ML • PA via detecting and predicting low-concentration, complex VOC mixtures of food-borne pathogens in the field
E-nose combined with ML (Pulluri and Kumar, 2022)	**Product (i.e., beef) quality control;** the design is proposed for effective classification of beef quality and prediction of microbial population in beef.	• DC via e-nose, • DA via ML • CA and PA via quality classification of beef and providing feedforward information for microbial population prediction in beef
A combination of High-Precision LCR meter (inductance, capacitance, and resistance) with ANNs (Mohammed et al., 2022a)	**Product (i.e., date palm fruit) quality control;** The aim is to predict quality attributes of date palm fruits during cold storage based on 14 electrical properties.	• DC via physicochemical and electrical properties analyses) • DA via ANNs • PA via feed-forward ANNs with a back-propagation training algorithm for the prediction quality of date palm fruit
Magnetic Resonance Imaging combined with ML (Torres et al., 2022)	**Product (i.e., beef and pork meat) quality control;** The aim is to predict quality characteristics as completely as possible to offer the meat industry an alternative solution to	•DC via physicochemical, instrumental textures and sensory analyses • DA via ML • PA via prediction of quality by physicochemical quality characteristics of pork and beef loins in four

(*continued on next page*)

Table 1 (*continued*)

Technology*	Type of quality control and aim of the design	Application of technology in Quality Control Circle#
	physicochemical and sensory methods.	meat states (fresh, thawed, cooked, and cured).
A low-cost imaging system with a digital camera coupled with DNN (Setiadi et al., 2022)	**Product (i.e., meat) quality control;** The design is proposed for adulteration detection in minced beef.	• DC via capturing of images with a low-cost camera system • DA via DNN • CA and PA via adulteration predictions based on colour and texture features
Computer vision system combined with ANN (Hosseinpour and Martynenko, 2022)	**Product (i.e., shrimp) quality control;** The design aims for the real-time evaluation of food quality, which is explained as a multi-dimensional variable with objective and subjective (e.g., consumer perception, which are fuzzy values) elements.	• DC via real-time measurements of quality attributes with computer vision • DA via processing of the measurable quality attributes using ANN • CA and PA via using the real-time quality attributes' predictions of the drying shrimp
The camera integrated with DNN (Wang et al., 2022)	**Product (i.e., rice) quality control;** The design aims to automatic visual quality estimation of rice kernels.	• DC via camera • DA via DNN • CA via quality estimation of rice according to kernel flaws classification
A combination of E-nose with CNN (Yan and Lu, 2022)	**Product (i.e., rice) quality control;** The design is proposed to classify the rice origin and detection of rice quality.	• DC via an e-nose system • DA via classification of rice origins with CNN, which can reflect the overall rice quality
Infrared thermography camera integrated deep learning ((Estrada-Pérez et al., 2021)	**Product (i.e., rice) quality control;** The design aims to classify five different types of rice in grain or flour format and detect mixtures of different rice types which act as adulterated samples and to ensure quality and safety.	• DC via thermographic camera • DA via DL by classifying five types of rice of different quality • CA and PA via detecting potential adulterations resulting from the different rice mixtures
Neural network integrating an analytic hierarchy process approach and the entropy weight (AHP-EW) (Geng et al., 2021)	**Product (i.e., meat) quality control;** The design aims to provide an early warning approach for assessing and controlling food safety risks.	• DA via the NN, heavy metal, microbial, and food additive indexes of the meat product are compared with the threshold indexes • PA via early detection and predictions of food safety issues, and taking measures to prevent potential risks
E-nose combined with ML (Viejo et al., 2020)	**Product (i.e., beer) quality control;** the design aims to develop a portable, low-cost model for assessing beer quality based on their aroma composition	• DC via real-time measurements of volatile aromatic compounds with e-nose • DA via analysis of e-nose data by ML models • CA and PA via provided predictions of important volatile aromatic compounds and intensity of sensory descriptors
DoFP polarisation camera combined with ML (Takruri et al., 2020)	**Product (i.e., apple) quality control;** the design aims to estimate the freshness and quality of apples in terms of age non-invasively and determine if they are fit for consumption even before the external rot appears on the fruit.	• DC via camera • DA via comparing the changes in polarisation properties of samples over time • CA and PA via automated prediction of freshness and quality
The thermographic camera combined with DL (Izquierdo et al., 2020a)	**Product (i.e., honey) quality control;** The design aims for qualitative and quantitative detection of rice syrup in honey (≤8 % in w/w) as an alternative to current quality control systems and fraud detectors.	• DC via capturing of thermographic images of the cooling process of honey samples • DA via the neural network to the classification of honey • CA and PA via detection and quantification of honey adulteration
The thermographic camera combined with DL (Izquierdo et al., 2020b)	**Product (i.e., extra virgin olive oil) quality control;** The design aims to detect adulterations by comparing the thermographic profiles of pure and adulterated extra virgin olive oil (EVOO) during its cooling process.	• DC via capturing of thermographic images of the cooling process of samples • DA via the NN • CA and PA via detection and quantification of adulteration
FTIR spectroscopy and MSI coupled with ML (Fengou et al., 2020)	**Product (i.e., minced pork meat) quality control;** The design aims to assess meat microbiological quality.	• DC via FTIR and MSI instruments and microbiological tests • DA via the developed ML models • CA and PA via estimation of the microbial population
A combination of acoustic frequency responses with parallel CNN-RNN and CRNN models (Iymen et al., 2020)	**Product (i.e., dairy) quality control;** The design aims to identify dairy products with or without non-dairy additives (NDA), and additionally distinguishing organic food products from non-organic ones.	• DC via designed set-up with speaker and microphone • DA via the developed NNS • CA and PA actions via detecting non-dairy and non-organic additives
A portable and compact E-nose combined with a NN (Gamboa et al., 2019)	**Product (i.e., wine) quality control;** The design aims for the early detection of wine spoilage thresholds in routine tasks of wine quality control.	• DC via E-nose • DA via the developed NN models to classify the quality of wines
Computer vision system and NIR combined with ML (Geronimo et al., 2019)	**Product (i.e., chicken breast meat) quality control;** The design aims to identify and classify wooden chicken breasts (WB) meat which is characterised by reduced meat quality related to undesirable changes in visual aspects, technological characteristics, and nutritive properties.	• DC via camera in the computer vision system • DA via the developed ML classifiers to detect normal and WB samples
ANN combined with images taken by smartphone (Hosseinpour et al., 2019)	**Product (i.e., fresh beef) quality control;** The design aims to estimate the tenderness and quality of the fresh beef sample from its real-world image.	• DC via smartphone camera • DA via the developed BeefQuality app where the meat images are processed in real time according to the proposed algorithm • PA via predicting beef tenderness and quality from its real-world image

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Table 1 (*continued*)

Technology*	Type of quality control and aim of the design	Application of technology in Quality Control Circle#
E-nose combined with ML (Ordukaya and Karlik, 2017)	**Product (i.e., olive oil) quality control;** The design is proposed for the classification of olive oils for quality control.	• DC via E-nose • DA via ML to identify and classify olive oil types and quality
Digital cameras combined with ML (Olaniyi et al., 2017)	**Product (i.e., banana) quality control;** The design aims to classify the banana as a healthy or defective banana and to solve the inaccurate standard quality product in the fruit processing industry.	• DC via digital camera • DA via ML to in-line quality control of bananas by sorting them based on the quality standards
A computer vision system combined with ML (Moallem et al., 2017)	**Product (i.e., apple) quality control;** The design aims to evaluate apple quality based on the surface features	• DA via ML to classify apple quality
Artificial Intelligence – Implementation status: Field-tested		
A Contrastive Self-supervised learning-based Graph Neural Network (CSGNN) framework Yan et al. (2023)	**Product (i.e., dairy) quality control:** The design aims contamination warning and food quality control	• DA via NN • CA and PA via early warnings for contamination
Image processing and computer vision techniques combined with ML (Zia et al., 2022)	**Product (i.e., rice) quality control;** The aim is to assess rice grain quality using a non-destructive and inexpensive approach which also presents Pakistan's first commercial automated rice quality assessment system	• DC via flatbed scanner hardware • DA via ML • CA and PA via assessing and controlling the quality of the dry kernel
Image sensors combined with deep CNNs (Zhang et al., 2020)	**Process (i.e., cane sugar crystallisation stage) quality control;** The design aims to classify the cane sugar images during the crystallisation process which can affect the final sugar product quality	• CA and PA via NN classification (the degree of vacuum; steam pressure; concentration of the feed; and the concentration of the syrup in the sugar tank can be arranged, and automatic control of the crystallisation stage can increase the quality of the last sugar product)
IoT & Cloud – Implementation status: Laboratory-tested		
Cloud-based IoT system combined with sensors (Mishra et al., 2023)	**Process (i.e., food drying parameters) quality control;** The design aims to remote control, alert of imminent hazards, monitor the microclimate parameters and investigate the effects of the developed system on the quality of dried leafy vegetables.	• DC via temperature, internal relative humidity (RH), and airflow rate sensors, IoT and cloud systems • DA via data analytics with MATLAB • CA via remote and automatic regulations of the heater, exhaust fan, and humidification unit with the microcontroller based on readings of sensors, and PA via the alert that is sent based on real-time data analytics through a private channel on the cloud platform.
IoT-enabled e-nose system (Damdam et al., 2023)	**Product (i.e., meats and fresh produce) quality control;** The design aims to monitor food quality by evaluating the concentrations of volatile organic compounds (VOCs) and identifying beef spoilage.	• **DC via E-nose carbon dioxide, ammonia, and ethylene gas levels, temperature and humidity sensors and IoT** • **CA via a user interface for real-time monitoring**
Cloud-based IoT interconnected to sensors (Mohammed et al., 2022b)	**Process (i.e., date fruit cold storage storage) quality control;** The design aims to remote control, provide risk alerts, and monitor the microclimate parameters in a cold storage room.	• DC via sensors for RH, temperature, CO2, C2H4, light, temperature, electrical current, and energy consumption, and IoT • DA via data analytics with MATLAB • CA via controlling if the system works, and sending alerts in cases of emergency
IoT & Cloud – Implementation status: Field-tested		
State-of-the-art smart production control system that utilises IoT, big data analytics, ML, cyber-physical systems and cloud computing (Konur et al., 2023)	**Process (i.e., baking) quality control;** The design aims to transform the production processes to produce good quality products based on real-time data-driven decision-making models.	• DC via sensors, probes and IoT • DA via big data and ML • CA and PA via real-time data monitoring, predicting the best baking conditions inside the ovens and enhanced decision-making
Big data & Data mining– Implementation status: Laboratory-tested		
RFID combined with IIoT, data mining and ML (Song et al., 2024)	**Process (i.e., environment monitoring) and product (i.e., ham) quality control;** The design aims to implement real-time environmental monitoring, item-level multi-sensing, effective food quality assessment and prediction, and information traceability	• DC via RFID sensors and IIoT • DA via big data and ML • CA and PA via assessment of food product freshness and prediction of food shelf life
Data mining and DL (Zhou et al., 2023)	**Product (i.e., wine and glutinous rice cake) quality control;** The designed system is proposed to realise the standardisation and consistency of food quality assessment and to achieve or exceed the accuracy of existing technologies.	• DA via data mining to find the optimal neural network assessment model
Big data & Data mining– Implementation status: Field-tested		
Data mining with the Apriori algorithm (Jacobsen and Tan, 2022)	**Process quality control;** The design proposes an integrated quality monitoring system with enhanced data visualization which can assist quality managers in making informed food safety decisions.	• CA and PA via investigation of quality issues at their root and taking effective measures
The data mining with the Apriori algorithm (Wang and Yue, 2017)	**Process (i.e., transit time, temperature, season, conveyance, package, product type, and customer satisfaction) quality control;** The design aims to timely monitor all the detection data, automatically pre-warn and find food safety	• CA and PA via highly effective real-time food safety risk monitoring and pre-warning

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Table 1 (*continued*)

Technology*	Type of quality control and aim of the design	Application of technology in Quality Control Circle#
	risks in advance, and give some decision-support information to maintain the quality and safety of food products.	
Blockchain – Implementation status: Field-tested		
Smart contracts on Blockchain (i.e., Ethereum) combined with ML (Yu et al., 2020)	**Product (i.e., peach juice) quality control;** The design is proposed for an intelligent quality monitoring system for fruit juice production.	• DC via smart contracts on the blockchain • DA via ML (comparison of the outcome value and specified threshold) • CA and PA via the message that the system sends to terminate the production process or a message stating that this batch of samples meets the standard created and stored on the blockchain

* The 'technology' term involves any I.4.0 technology that is used or combined with other tools in quality and safety control systems in food manufacturing.
# ***DC: data collection; DA: data analysis; CA: corrective actions; PA: proactive actions.***
RFID: radiofrequency identification; **IIoT**: Industrial Internet of Things; **ML**: Machine learning; **DL**: Deep learning; **AI**: Artificial Intelligence; **μPD-OES**: point discharge microplasma optical emission spectrometer; **SPME**: solid phase microextraction; **NIR**: near infra-red; **VIS-NIR**: visible near infra-red; **SWIR**: short wave infra-red reflectance; **FL**: fluorescence; **GC-MS**: Gas Chromatography Mass-Spectroscopy; **NN**: neural network; **ANN**: artificial neural network; **DNN:** deep neural network; **CNN**: convolutional neural network; **AHC-RBF**: agglomerative hierarchical clustering-radial basis function; **CNN-RNN**: combination of convolutional neural network-recurrent neural networks; **CRNN**: convolutional recurrent neural network; **HPLC**: by High Performance Liquid Chromatography; **MRI**: Magnetic Resonance Imaging; **MSI**: multispectral imaging; **DoFP**: Division-of-Focal-Plane; **MSI**: multispectral imaging.

intervention, and risk assessment by predicting potential issues based on current data. The detailed working principle of each proposed I4.0 technology implementation can be found in the supplementary file in Table S4.

Table 1 shows that the most studied I4.0 technology is AI, which conceptually encompasses machine learning as a subfield, deep learning as a type of machine learning, and neural networks as it is used in deep learning (Soori et al., 2023). Similarly, Yu et al. (2025) highlighted the growing necessity and interest in AI integration in food systems, driven by the 2022 Global Food Security Index (GFSI) call, which underscores declining global food security impacting nearly a third of the population. Despite this, most AI-related studies (26 out of 29) are at the laboratory-tested status (e.g., Ren et al., 2024; Squara et al., 2023; Yan and Lu, 2022), suggesting that AI's practical in-field applications in food quality and safety control systems are still evolving. Furthermore, almost all of the proposed AI implementations are used for quality control purposes of products, e.g., coffee (Przybył et al., 2023; Ren et al., 2024), beer (Viejo et al., 2020), dairy (Iymen et al., 2020; Yan et al., 2023), meat (Pulluri and Kumar, 2022; Torres et al., 2022; Setiadi et al., 2022; Ren et al., 2024), honey (Izquierdo et al., 2020a; Chenchouni and Laallam, 2024), rice (Wang et al., 2022; Yan and Lu, 2022; Estrada-Pérez et al., 2021), fruits (Olaniyi et al., 2017; (Mohammed et al., 2022a-b) and olive oil (Ordukaya and Karlik, 2017; Izquierdo et al., 2020b) rather than the processes. This might show that the implementation of AI technologies nowadays is driven by the demand for ensuring end-product quality and safety.

Most AI implementations in food quality and safety control systems involve various types of cameras (e.g., digital, thermographic, polarisation, and smartphone) to mainly identify quality classes (Przybył et al., 2023; Olaniyi et al., 2017), detect adulteration (Setiadi et al., 2022; Estrada-Pérez et al., 2021), and predict quality and safety (Hosseinpour et al., 2019; Wang et al., 2022) through food product images. In these studies, AI models are trained using these images alongside datasets from analytical or sensory techniques for quality and safety predictions. Another common tool combined with AI is the electronic nose (E-nose) (Table 1), which detects volatile compounds in samples via interactive sensors and converts this data into digital outputs for statistical analysis (Jiang et al., 2025). The majority of designs in the reviewed studies aim to assess and classify quality (Pulluri and Kumar, 2022; Yan and Lu, 2022; Viejo et al., 2020; Ordukaya and Karlik, 2017) and predict the microbial population (Pulluri and Kumar, 2022; Gamboa et al., 2019) by training AI with volatile component data and datasets from chemical, microbiological, instrumental, and sensory tests.

The results also show that while integrated tools are used for the *data collection* element of the quality control circle, AI technology mainly serves the *data analysis* element (Table 1**).** In the majority of the reviewed studies, the obtained outputs and results through I4.0 technology implementation can also support the *corrective and proactive action* elements of a control circle, which may show the promising role of AI in transforming raw data in an actionable manner and bridging the gap between data collection and decision-making. For instance, Zhang et al. (2023) developed an ML-assisted Raman spectroscopy system that predicts microbiological quality by simulating a spoiled food environment through fingerprint volatile organic compounds (VOC). The results demonstrated the potential of the designed system for real-time classification of foodborne pathogens, even at low concentrations and within complex VOC mixtures. This application can enable proactive measures such as preventing contaminated products from being released to the market and reaching consumers. In another study, Iymen et al. (2020) integrated an acoustic frequency dataset with deep learning models to detect non-dairy additives in dairy products, enabling proactive identification of nonconformities such as fraud or contamination and facilitating corrective actions.

IoT and cloud systems are other widely studied I4.0 technologies in quality and safety control systems (Table 1). As a key I4.0 technology, IoT enables communication between smart devices for measuring, collecting, and analysing variables (Balali et al., 2020; Hassoun et al., 2023a-b). IoT and cloud designs are often integrated with sensors and tools to control process parameters (e.g., in drying, cold storage, baking), addressing all elements of the quality control cycle (i.e., *data collection, data analysis, corrective or proactive actions*). However, most reviewed studies on IoT indicate laboratory-scale implementations with limited field applications (Damdam et al., 2023; Mishra et al., 2023; Mohammed et al., 2022b). This result might show that, although IoT is not a new technology, its practical utilisation in the frame of the I4.0 concept is still in the early phase for food quality and safety control systems. Similarly, Bouzembrak et al. (2019) reviewed the potential applications of IoT in food safety and concluded that it remains a relatively novel approach. They stress that, in most studies, proposed IoT architectures are primarily theoretical constructs with limited real-world implementation, indicating that practical applications in food safety are still rare. Besides, they highlight that, according to Talavera et al. (2017), IoT applications in agriculture and the food sector are still in their early stages of development.

Similar to IoT, big data and data mining, which are often combined with other technologies, are predominantly proposed for controlling process quality and safety parameters instead of products. Big data is the immense amount of digital information generated through various digital devices, and data mining involves uncovering hidden patterns and relationships within this large volume of raw data (Che et al., 2013). These technologies mainly support data analysis and corrective and proactive action elements of the quality control circle (Table 1). For example, Jacobsen and Tan (2022) designed and implemented a data mining prototype to process large volumes of incident data to create

Table 2
The identified main technical/technological and managerial categories of the benefits of the Industry 4.0 technology implementations into quality and safety control systems in food manufacturing.

Sub-categories	Explanation	AI	IoT and Cloud systems	Big data and Data mining	Blockchain
Technical/Technological Benefits					
Contamination detection and reliable food safety and quality prediction	I4.0 technologies or their combination with other tools could provide efficient and high-accuracy prediction, detection and early warning of contaminated samples, microbial populations, and foodborne pathogens and provide freshness evaluation and quality prediction with robust statistical accuracy.	24	3	2	1
Real-time quality assessment and prediction, rapid and effective quality monitoring and control	I4.0 technologies or their combination with other tools could provide live and in-system assessment, effective sensing, and prediction of food quality and safety and deliver immediate results with efficient identification, classification, and estimation in minimal computational time.	23	1	2	–
Adaptability and usability with other food products, industries and technologies	I4.0 technologies can offer adaptive systems with flexibility for integration into various technologies, different food products and food sectors and be open to a range of development opportunities.	11	1	3	1
Ability to classify the quality of food samples	AI or its combination with other tools can provide precise and effective classification of different species, spoilage levels, and adulteration.	13	–	–	–
Regular or continuous monitoring and controlling of the quality parameters and operations	I4.0 technologies and their combination with other tools could provide continuous recording, monitoring and control of process parameters and operations that are related to food safety and quality.	6	3	1	1
Adulteration and fraud detection	AI, IoT and cloud technologies or their combination with other tools could be designed for the effective detection and quantification of food adulteration, helping prevent food fraud. They could identify adulterants in various products, such as beef, olive oil, and dairy, distinguishing between authentic and adulterated goods, including those with harmful substances.	8	1	–	–
Non-destructive quality control	AI, IoT and cloud technologies or their combination with other tools could provide non-invasive, non-destructive, and contactless techniques for quality monitoring, assessment, and estimation without altering or damaging the food sample.	7	1	–	–
Supporting decision-making and rapid response on food quality and safety	I4.0 technologies and their combination with other tools could provide operators with critical information, enabling quick and effective responses to changes and potential issues while supporting more informed decision-making in quality control processes.	3	3	2	–
Supporting product quality enhancement and assurance	I4.0 technologies and their combination with other tools could support overall product quality improvement, maintaining consistency and assurance	2	3	1	–
High-degree automated quality control	I4.0 technologies and their combination with other tools could achieve a high level of automation in quality control by replacing tedious, error-prone manual tasks, and enhancing efficiency, accuracy, and consistency in the process.	2	3	1	1
Portable and able to on-site quality evaluation and inspection	I4.0 technologies and their combination with other tools could be portable and be able to on-site quality evaluation and inspection.	4	–	–	–
Enhancing current quality control systems	I4.0 technologies and their combination with other tools could improve the capabilities of integrated quality control processes and increase the overall quality testing capacity.	1	1	1	–
Reference architecture for standardized quality assessment	I4.0 technologies and their combination with other tools could provide a reference framework that establishes standards in the field of food quality assessment, facilitating the creation of a unified and optimal assessment model.	–	1	1	–
Managerial Benefits					
Cost-effectiveness and preventing additional financial losses and expenses	I4.0 technologies and their combination with other tools could be cost-effective, focusing on reducing financial penalties, minimizing expenses, and optimizing resource use through strategies like reducing human labour, minimizing financial and time costs, developing low-cost components, and preventing additional losses (e.g., food recalls and product returns).	7	3	3	1
Better food safety and crisis management	AI, big data and data mining technologies and their combination with other tools could support taking effective measures for food safety and crisis management and help establish emergency mechanisms, a priority system for hazard analysis and effective measures for safety regulation by analysis of results.	3	–	3	–
Strategy improvement	Mainly AI, big data and data mining technologies and their combination with other tools could support optimizing manufacturing and warehousing strategies while enabling improvements in supply chain management. They could be useful in guiding strategic investments and shaping value chains to enhance competitiveness. Additionally, they could support food safety control strategies based on scientific principles.	3	1	2	–
Traceability and Communication Enhancement	AI, big data and data mining technologies and their combination with other tools could make implicit knowledge explicit, provide valuable insights, improve communication and information sharing, and support the traceability of both quality and information.	1	1	3	–
Objective and Unified Decision-Making	I4.0 technologies and their combination with other tools could enhance decision-making by ensuring objectivity, minimizing human intervention, and reducing risks associated with manual operations.	2	2	1	–
Simplified, user-friendly, and low-stress operations	I4.0 technologies and their combination with other tools could have low operational complexity, be straightforward, have no occupational risk, be user-friendly, reduce stress and fatigue, and make it easy for regular users to operate with minimal training.	2	2	1	–
Optimisation of manufacturing and quality control systems	AI, big data and data mining technologies and their combination with other tools could help optimise manufacturing lines and enhance the effectiveness of food safety and quality control systems by providing powerful information.	1	–	1	–

(*continued on next page*)

Table 2 (*continued*)

Sub-categories	Explanation	AI	IoT and Cloud systems	Big data and Data mining	Blockchain
Technical/Technological Benefits					
Technology-driven transformation and culture change	AI and its combination with other tools could support the business's shift toward a technology-driven approach, fostering a cultural change that embraces innovation.	–	1	–	–

Numbers represent the count of studies that mentioned corresponding benefits out of a total of 38 articles.
Details of references per technology can be found in Table S5 in the supplementary materials.

transferable insights within food safety and quality management systems. They introduced a sensor-based system that analyses over 4000 alarms from a fast-food franchise, monitoring food quality, environmental conditions, and corrective actions. Equipped with 37 alarm attributes, the system provides real-time data access via a dashboard, enabling quality managers to receive alerts on limit violations and implement proactive quality control measures. In another study, Wang and Yue (2017) developed a food safety pre-warning system for dairy producers, integrating data mining technology to support managerial decision-making. The system processes food safety data from production, processing, and transportation, identifying warning rules based on frequent item sets. By leveraging temporal and causal relationships, the system enables proactive risk detection, with identified abnormalities triggering emergency feedback mechanisms to facilitate timely intervention. Although the reviewed literature shows a balance between laboratory and field-tested applications (Table 1), Marvin et al. (2017) and Jin et al. (2020) note that despite its potential and successes in predicting, monitoring, and controlling food safety, big data implementations are still limited and scarce.

Blockchain shows promise for the food industry but is mainly applied to food supply chain traceability (e.g., Arvana et al., 2023; Dey et al., 2021; Yang et al., 2021), not food manufacturing. Similarly, digital twins and 3D printing are used in the agri-food sector for cold food chain and transport/distribution, and product development (Defraeye et al., 2019; Grazioli et al., 2020), with no studies linking them to food quality and safety control in manufacturing.

The literature review results show that I4.0 technologies are mostly integrated with other instruments and tools and are still at the laboratory-tested implementation stage. To advance the implementation of field-tested technologies into food quality and safety control, the benefits must be clearly communicated and barriers addressed through a multidisciplinary approach. Luning and Marcelis (2006, 2009) stressed the need to concurrently analyse technological and managerial perspectives to achieve a more comprehensive and nuanced understanding, while Rizzuto and Reeves (2007) highlighted information technology (e.g., software, database and communication systems) implementations require multidisciplinary research spanning technological, organisational, and human factors.

4. Benefits of industry 4.0 technologies in food quality control and safety systems

Table 2 presents the identified technical/technological and managerial benefits in the reviewed studies. The most reported technical/technological benefit is *contamination detection and reliable food safety and quality prediction ability*. All Industry 4.0 technologies contribute to this benefit, with AI being the most prominent. Studies demonstrated that various I4.0 technologies could effectively predict, detect and early warn the contaminated samples (Geng et al., 2021; Yan et al., 2023), microbial populations (Pulluri and Kumar, 2022) and foodborne pathogens (Zhang et al., 2023), and provide freshness evaluation (Ren et al., 2024; Song et al., 2024) and quality prediction (Geronimo et al., 2019; Przybył et al., 2023) with good statistical accuracy. For instance, Geng et al. (2021) developed an AI-based early warning system for assessing and controlling food safety risks, demonstrated through a case study on meat product detection data. The system preprocesses inspection data on heavy metals, microbiological contaminants, and food additives, and then calculates risk values based on proximity to standard maximum limits. A neural network model predicts risk levels from the processed data, enabling early warning threshold applications for risk analysis with good accuracy. The study highlights AI's potential in reliable food safety prediction. The other most reported technical/technological benefit is *real-time quality assessment and prediction, rapid and effective quality monitoring and control,* which point out that I4.0 technologies like AI, IoT and big data could provide real-time assessment of quality and safety, and deliver immediate results (Table 2). For example, Viejo et al. (2020) integrated ML into an e-nose system for real-time beer quality prediction based on aroma compounds, while Mishra et al. (2023) applied IoT in a food dryer for real-time and remote monitoring of drying parameters in coriander and mint leaves, directly impacting final food quality. Viejo et al. (2020) concluded that the developed ML-integrated e-nose system is a reliable and effective tool for real-time quality assessment, with potential use in production lines. Similarly, Mishra et al. (2023) suggested that IoT-enabled drying systems can identify issues in real time and automatically adjust drying parameters based on real-time data, thereby facilitating remote monitoring and allowing operators to track drying cycles.

Several studies highlighted the benefit of *adaptability and usability with other food products, industries and technologies*. For instance, Damdam et al. (2023) proposed an IoT-enabled e-nose to analyse volatile organic compounds and detect beef spoilage, noting its applicability to other meat types, fruits, and vegetables. Similarly, Izquierdo et al. (2020b) developed an AI-integrated thermographic camera system for detecting and quantifying adulterations in extra virgin olive oil, emphasising its potential use across diverse food products and industries.

AI's *ability to classify the quality of food samples* is a widely reported benefit (Table 2), enabling the classification of different species (Yan et al., 2023; Ren et al., 2024; Chenchouni and Laallam, 2024), spoilage levels (Gamboa et al., 2019), and adulteration (Izquierdo et al., 2020a). For instance, Chenchouni and Laallam (2024) combined neural networks with traditional analytical techniques to classify honey samples based on origin, honeybee breed, extraction method, and beekeeping systems. The developed neural network system effectively classified the samples based on these factors, demonstrating its applicability for food quality assessment. *Regular or continuous monitoring and controlling of the quality parameters and operations* is another key benefit (Table 2). Saihi et al. (2021) noted that I4.0 technologies enable real-time monitoring, improving root cause identification and process control. For instance, Yu et al. (2020) demonstrated a system that continuously monitors quality parameters through a three-step process: optimisation, data recording, and quality evaluation. During the optimisation process, optimal conditions are identified using response surface models based on pre-production data, such as volatile compound analysis. In the data recording process, smart contracts record key process data during production on a blockchain system, which serves as the input for evaluation models. In the quality evaluation process, another smart contract evaluates the recorded data using statistical models to assess quality and detect contamination risks after each production stage. If quality drops below a predefined and recorded threshold in the blockchain, the process automatically halts, ensuring continuous control of the quality parameters and operations.

The literature highlights numerous technical/technological benefits, while managerial benefits are less frequently addressed. The most commonly reported managerial benefit is *cost-effectiveness and preventing additional financial losses and expenses* (Table 3). Implementation of I4.0 technologies can reduce penalties, minimise expenses, and optimise resource use through strategies like reducing human labour (Zhang et al., 2020; Konur et al., 2023), minimizing financial and time costs (Yan et al., 2023), developing low-cost components (Setiadi et al., 2022; Zia et al., 2022), and preventing additional losses (e.g., food recalls and product returns) (Wang and Yue, 2017; Yu et al., 2020). For instance, Yan et al. (2023) developed an AI-based early warning system for contamination detection in dairy based on physicochemical (i.e., lactose, non-fat milk solids, protein, acidity, and fat) and mycotoxin indexes (i.e., aflatoxin), which help reduce economic losses, including financial penalties and reputational damage, by improving food safety and quality control. Another managerial benefit is *better food safety and crisis management* through technologies such as big data, data mining, and AI, which enable effective food safety and crisis management supporting emergency response systems(Jacobsen and Tan, 2022), and enable data-driven priority systems for hazard analysis (Wang and Yue, 2017; Yan et al., 2023). *Strategy improvement* is also noted as a benefit of these technologies enhancing manufacturing and warehousing strategies and improving supply chain management (Squara et al., 2023; Song et al., 2024). Additionally, they can guide strategic investments (Konur et al., 2023), shape value chains to strengthen competitiveness (Squara et al., 2023; Wang and Yue, 2017), and support the development of food safety control strategies based on scientific principles (Yan et al., 2023). Squara et al. (2023) developed an AI-based augmented smelling machine utilising volatile quality markers (e.g., key aroma compounds, spoilage odorants, rancidity levels, and origin tracers) to assess raw hazelnut quality. They proposed that this technology implementation could serve as a decision-making tool, guiding strategic industry investments and shaping value chains. In another study, Song et al. (2024) proposed a data mining technology with AI combination for ham quality

Table 3
The identified main and sub technical/technological and managerial categories of barriers to the Industry 4.0 technology implementations in quality and safety control systems in food manufacturing.

Main categories	Sub-categories	Explanation	AI	IoT and Cloud systems	Big data and Data mining	Blockchain
Technical/Technological Barriers						
Product-related barriers	Product or dataset-dependent models and system limitations	The developed models or implemented advanced technologies may be dependent on specific products, or product quality datasets and need reconfiguration or retraining steps to adapt.	5	–	1	–
Process and equipment-related barriers	High-quality data and time investment requirements	The development and optimisation of models may need significant time and computational resources, especially when handling large datasets or numerous quality attributes. High-quality, diverse, and well-balanced data are necessary to ensure more reliable outcomes.	5	2	2	–
	Performance and accuracy optimisation needs	Achieving reliable, accurate, and efficient model performance is still open to improvements due to issues like overfitting, misclassification, and imbalanced or low-quality datasets. There is a need for further optimisation, exploration of additional features, and advanced methods to improve predictions.	5	–	2	1
Production-related barriers	Effects of external and environmental factors on system performance and accuracy	Variations in environmental factors (e.g., ambient lighting, noise, or unstable measuring conditions) can adversely affect results and reliability.	3	–	1	–
	Infrastructure and integration difficulties into traditional or outdated systems	Incorporating advanced technologies into traditional or outdated systems may be a barrier because of the lack of pre-existing infrastructure for these technologies. Also, the absence of off-the-shelf integration solutions can further complicate the transition to digitalisation.	–	3	–	–
Managerial Barriers						
People-related barriers	Human-based errors and security concerns	In AI and IoT technologies and their combination with other tools, the quality and quantity of model training data labelled by non-professionals can cause inaccuracies and inconsistencies. Besides, improper handling or interpretation of personal or sensitive data may raise security concerns.	2	1	–	–
	Ethical and social implications	Over-dependence on Industry 4.0 technologies can result in unemployment. Additionally, conflicts of interest may arise when these technologies are used to harmonize processes and decisions across diverse groups, such as customers and company-internal departments, whose priorities and objectives may not align.	–	1	1	–
	Needing to improve user understanding and acceptance of technology	Big data and data mining technologies and their combination with other tools may require users to grasp complex concepts, such as the interpretation of outputs of these technologies, which can be challenging without sufficient training or expertise. Limited understanding can be a barrier to the acceptance of these technologies.	–	–	1	–

Numbers represent the count of studies that mentioned corresponding benefits out of a total of 38 articles.
Details of references per technology can be found in Table S6 in the supplementary materials.
Product-related: barriers to technology implementation related to inherent food product features; **Process and equipment-related**: barriers to technology implementation related to process parameters and equipment features; **Production-related:** barriers to technology implementation related to internal circumstances of the production facilities, buildings and factories and external environment circumstances (climate, geography etc); **People-related:** barriers to technology implementation related to decision-making behaviour, commitment and competencies.

assessment and prediction. They suggested that this system could optimise warehousing strategies by monitoring quality loss, while also improving supply chain management by providing traceability information and key physical parameters to supply chain managers and manufacturing line controllers.

However, while technical/technological benefits are typically based on practical applications, managerial benefits are often theoretical or suggested rather than observed. This underscores the need for further research, particularly multi-case studies, to better understand the managerial impacts of I4.0 technologies in this domain.

5. Barriers to industry 4.0 technologies in food quality control and safety systems

Despite all the benefits, several studies highlighted some barriers to implementing these technologies into control systems. Identified barriers were examined as technical/technological and managerial, and to provide a holistic understanding of implementation barriers, they were further grouped into main categories, e.g., product-related, process and equipment-related, production-related, or organisational-related and people-related.

A key technical/technological barrier is the need for *high-quality data and time investment requirements* for data processing, model training and computations, which is categorised as a process and equipment-related barrier (Table 3). AI implementation can be time-intensive and computationally demanding, particularly when handling large-quality datasets or multiple-quality attributes. Yu et al. (2025) identified data quality and algorithmic transparency as challenges in AI adoption for food safety. Chhetri (2024) emphasised that the precise food quality and safety predictions by AI models highly depend on the amount of high-quality data in the training phase. For instance, Konur et al. (2023) found that while integrating data across a factory improved process coverage, it increased model complexity and slowed training. Similarly, Izquierdo et al. (2020b) pointed out that AI training and optimisation stages need high computational resources, which can make it slow in those stages. Zhang et al. (2023) further discussed the importance of high-quality and well-labelled datasets, demonstrating through Raman spectroscopy data that better labelling is essential for improving machine learning predictions.

Furthermore, Table 3 shows *performance and accuracy optimisation needs*, as a barrier, especially for AI, big data and data mining technologies to address issues such as overfitting and misclassification. For instance, Setiadi et al. (2022) found that their developed imaging-based adulteration detection system for minced beef, using a digital camera combined with machine learning, was less accurate than other techniques (e.g., hyperspectral imaging), suggesting more extensive data training was needed for better performance. Another barrier is *product or dataset-dependent models and system limitations*. This barrier is especially relevant for AI, big data and data mining technologies, which may need reconfiguration or retraining steps to adapt. Estrada-Pérez et al. (2021) proposed an infrared thermography camera-integrated ML technology for detecting adulterated rice samples, but concluded that for other types of rice or different additives, a new machine learning model must be trained. Similarly, Setiadi et al. (2022) noted that the technology they developed is limited to detecting surface adulterants in minced beef, and further research is needed to extend its applicability to different meat sources, origins, and other variables.

Table 3 also shows the managerial barriers, all of which emerged as people-related categories. Among these, ***human-based errors and security concerns*** have been most frequently mentioned. Manual data labelling by non-professionals can affect the quality and quantity of data and can cause inaccuracies and inconsistencies, particularly in AI-integrated technologies (Geronimo et al., 2019; Wang et al., 2022). Wang et al. (2022) highlighted this issue in their camera-integrated ML model for rice quality estimation, noting that non-expert labelling often has errors. Mishra et al. (2023) also warned that while IoT devices enable large-scale data collection, improper management can lead to privacy concerns, including the risk of sensitive information being misused or compromised.

Industry 4.0 technologies offer substantial benefits, but their adoption faces several barriers. Categorising these into product, process and equipment, production-related, and people-related aspects enables a more structured understanding and targeted solutions. However, our techno-managerial analysis shows that managerial perspectives, especially organisational and human factors, remain underexplored. Given their critical role in food quality management (Luning & Marcelis, 2020) and technology adoption (Rizzuto and Reeves, 2007), these aspects warrant greater research attention.

6. Conclusions and recommendations

This review highlights the role of I4.0 technologies in food quality and safety control at the manufacturing stage, with AI and IoT emerging as the most studied technologies. The findings indicate that AI is primarily used for product quality assessment, while IoT is more focused on process quality control. However, despite their potential, most implementations remain at the laboratory-tested stage, with limited real-world applications. Besides, while AI mostly contributes to the data analysis element of the quality circle, IoT supports the data collection element. The results also suggest that integrating I4.0 technologies with other tools may enhance their functionality and applicability.

The reviewed studies highlight that the mentioned benefits of Industry 4.0 technologies in food quality and safety are mostly technical/technological, with a strong focus on contamination detection, reliable food safety and quality prediction and real-time quality assessment and prediction -primarily enabled by AI, IoT, and big data. In contrast, managerial benefits like cost-effectiveness, enhanced food safety and crisis management, and strategy improvement are less explored and often discussed conceptually.

This study also highlights implementation barriers from the reviewed studies, with key technical/technological ones mainly related to *processes and equipment*. Notably, the need for high-quality data and the significant time required to train AI models, especially when handling large datasets or multiple quality attributes, stand out. Additionally, the studies emphasise that performance and accuracy optimisation still need improvement, particularly for AI implementations. Managerial barriers, though rarely discussed, are only *people-related*, such as human errors in manual labelling of data that are to be used with I4.0 technologies and security concerns that may arise from improper handling of data.

Despite growing interest, most of the reported I4.0 technologies remain at the laboratory-testing stage, with limited evidence on improving implementation efficiency and effectiveness. Since barriers are often case-specific and arise post-implementation, further research is needed to understand the organisational and technological conditions for effective implementation.

This review offers valuable insights for the food industry, quality control authorities, professionals, and technology developers, as it provides insight into not only current practices but also their multidisciplinary impacts. Possible implications of I4.0 technology implementations in food quality and safety systems may be more accurate, consistent, and real-time quality monitoring. For practitioners, this implies reduced human error and enhanced ability to prevent quality and safety issues proactively. For researchers, the findings highlight the need to further explore context-specific implementation strategies and the multidisciplinary factors influencing effectiveness and efficiency. Overall, these technologies hold significant potential to transform food quality and safety control, but their real-world application demands practical, technological, and organisational alignment.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to get inspiration for improved readability and compact writing at some points. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tifs.2025.105144.

Data availability

Data will be made available on request.

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