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Review

Food loss and waste reduction by using Industry 4.0 technologies: examples of promising strategies

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Abstract

Food loss and waste (FLW) represent a significant global issue, posing a threat to food sustainability on a worldwide scale. However, the growing awareness among consumers and the development of emerging technologies driven by the Fourth Industrial Revolution (Industry 4.0) present numerous opportunities to reduce FLW. This article provides a comprehensive examination of recently developed strategies for reducing FLW. The role of Industry 4.0 technologies, such as the Internet of Things, artificial intelligence, cloud computing, blockchain, and big data, is highlighted through examples of various promising initiatives. The results of this analysis show that the application of digital technologies to address the issue of FLW is on the rise globally, with Industry 4.0 technologies revolutionising many sectors, including the food sector. Further research is necessary, and closer collaboration between producers, distributors, consumers, and other actors involved in the food supply chain is still required to reduce FLW further.

Keywords: Industry 4.0, digital technologies, food waste, food loss, food supply chain

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Graphical abstract

Introduction

Food loss and waste (FLW) is a significant global concern. The amount of FLW is expected to increase by as much as 70% by 2050 if preventative measures are not implemented soon (Chen et al., 2020; Vittuari et al., 2019). FLW also has environmental repercussions for climate change, biodiversity loss, freshwater, marine and air pollution, and land (Guo et al., 2023). The United Nations' Sustainable Development Goal 12 aims to promote responsible consumption and production as well as reduce food waste by 2030.

FLW occurs at every stage of the food supply chain, from production to consumption, due to suboptimal harvesting practices, inadequate storage and transportation, over-purchasing, improper storage, and food perishability. Some FLW is generated at the manufacturing stage due to non-compliance with the food business' technical criteria, and when there is a lack of demand for produced foods at a certain time (Moldovan et al., 2024). For example, in a study of a prepackaged meal factory, it was determined that approximately 24% of FLW produced at the factory was due to overproduction or overstocking, resulting in ingredients exceeding their shelf life and spoiling (Jagtap & Rahimifard, 2019). Therefore, it is paramount to reduce FLW generation rates and implement promising strategies to valorise them. The primary objective of the circular economy is to maximise the efficient and comprehensive utilisation of all resources to minimise waste. Advanced technologies and innovations can support the circular economy (Herrero et al., 2020), and there are many examples to support this, for instance works on digital technologies (Benyam et al., 2021; Carlos et al., 2024; Rusch et al., 2023), and more specifically, smart sensors (Zhu et al., 2022), Internet of Things (IoT) (Kumar & Prashar, 2021), and nonthermal food processing (Arshad et al., 2022), among others. The fourth industrial revolution, also known as Industry 4.0, has introduced technologies that enhance production, support food traceability, improve food safety and quality, reduce FLW generation, and enable complete supply chain transparency from farm to consumer (Hassoun et al., 2022).

Industry 4.0 technologies can provide viable and secure solutions at every level of the food supply chain and enhance food sustainability and sustainable development goals (Kayikci et al., 2022; Oztemel & Gursev, 2020; Režek Jambrak et al., 2021; Simon et al., 2018; Sridhar et al., 2023). Although there is no common agreement on what technologies are included in Industry 4.0, most studies consider artificial intelligence (AI), IoT, smart sensors, big data, blockchain, and robotics as basic components of Industry 4.0 in agriculture and the food industry (Hassoun et al., 2022; Oztemel & Gursev, 2020; Senturk et al., 2023).

There is a growing amount of research about the potential of Industry 4.0 technologies for reducing FLW, for instance in recent works by Duong et al. (2024), Senguler and Kirkin (2024) and Wei et al. (2023). This article contributes to this growing body of knowledge by providing a comprehensive analysis of the Industry 4.0 technologies that can be used to reduce FLW and valorise surplus food and by-products across the entire food supply chain. It explores the interaction and relationship between sustainability and the key areas of Industry 4.0: traceability, process optimisation, and waste reduction. To analyse these applications of Industry 4.0 technologies, journal articles from the last five years were retrieved from Scopus database, based on a keyword search that included the technologies discussed in *Industry 4.0 technologies to reduce FLW*.

Industrial revolutions

Each technological advancement compels the industry to adapt to remain competitive. In the 19th century, the transition to innovative manufacturing processes marked the first industrial revolution or Industry 1.0. During this period processing changed from being human-dependent to mechanised using steam power (Yavari & Pilevari, 2020). The second industrial revolution (Industry 2.0) was based on mass production achieved by the division of labour and the use of electrical energy from the late 19th to late 20th centuries (Iyer, 2018). It enhanced food production, separation procedures, storage, and transportation. Using Industry 3.0, automation and digitalisation helped food companies build programmable and automated process lines, for example, baking lines. Food production was modernised, new packaging materials were developed, and promotional packaging was introduced (Lau et al., 2019). Additionally, Industry 3.0 helped reduce industrial FLW by utilising computerised food processing technologies. This enabled fresh foods to be cultivated in remote locations and made accessible for longer periods throughout the year. The fourth industrial revolution (Industry 4.0) of the present day, is exponentially expanding in scope and distinct domains of interest, including AI, blockchain, robotics, IoT, digitalisation, big data, autonomous vehicles, additive manufacturing, nanotechnology, biotechnology, and 3D food printing (Jideani et al., 2021). The technologies associated with Industry 4.0 have the potential to reduce FLW by tracking ingredients and quickly assessing various parameters (Hayat et al., 2023).

Industry 4.0 technologies to reduce FLW

Industry 4.0 unifies digital technologies to improve and automate the manufacturing process. The following is an overview of Industry 4.0-related technologies and their potential role in reducing FLW.

Big data

BD refers to large data sets (volume) generated at high rates (velocity), larger than what conventional data management systems can handle and store. These data sets are composed of data in a variety of data formats. In contrast, big data analytics (BDA) refers to applying advanced analytics to BD (Ciccullo et al., 2022), resulting in better interaction, planning, and control (Annosi et al., 2021; Hasan et al., 2024). The food industry generates enormous amounts of data, and BD has emerged as a leading technology for performance optimisation and traceability (Annosi et al., 2021; Rejeb et al., 2022). Based on massive data sets collected from various sources, BDA reduces FLW at each level of the supply chain as it determines the risk, solution, prevention, and control, and anticipates future challenges. The BD application processing system for the food industry is shown in Figure 1.

A suitable BD infrastructure is critical for transitioning to circular food supply chains and data analysis to reduce FLW with the help of BDA is essential for sustainable operations management in the circular economy (Kazancoglu et al., 2021; Rejeb et al., 2021). However, the potential of BD to reduce FLW in the food chain is not very well documented. A bibliometric analysis of household food waste, based on almost three thousand resources, revealed that most research is taking place in developed and emerging countries.

Kayikci et al. (2022) focused on food waste in the retail phase of the perishable food supply chain. They presented an optimal dynamic pricing strategy to adjust prices at different points in the sales season. In this solution, the unit price of products is updated continuously in response to real-time data on the product's shelf life (i.e., the state of freshness or deterioration).

Food prices are also influenced by economic factors such as the redistribution of excess supply. Establishing an effective pricing plan is essential to managing inventory and reducing excess food when demand is unpredictable. In this context, BDA assists managers by forecasting consumer behaviour and helping to establish price plans for the retail sector (Kayikci et al., 2022).

Despite its potential in the food supply chain, it can be said that the application of BD is still in its infancy (Tao et al., 2021). Some obstacles must be overcome for BD to reach maturity. These obstacles include issues with data equity, such as searchability, accessibility, interoperability, and reusability of shared data, as well as the lack of information standards and data processing technology (Tao et al., 2021). Currently, most organisations use BD as a descriptive or diagnostic tool and lack experience in its use as a predictive or prescriptive tool, which is an area of future development.

Internet of Things

Food-sensing technology, such as IoT sensors, can enhance food safety, quality, and traceability, thereby reducing FLW. In food manufacturing systems, IoT can assist manufacturers in identifying where food waste occurs by gathering and delivering real-time data, which can significantly influence efficiency and performance. Data provides insights that subsequently assist stakeholders in making key operational choices (Brabec et al., 2019; Kumar & Prashar, 2021). Thus, using IoT sensors, FLW can be tracked quickly and easily with little human input while providing economic and environmental data.

In food packaging, the use of smart labels, smart e-noses (a type of sensing system), real-time data tracking sensors, and radio frequency identification (RFID) technology are significantly contributing to effective FLW reduction and better management (Hasanin & Abdelkhalek, 2024). Implementing an IoT-based digital FLW monitoring system in ready-to-eat food production increases employee involvement and awareness and reduces FLW (Jagtap et al., 2019; Van et al., 2022). From a consumer perspective, the ability to communicate data through IoT reduces FLW. For instance, retailers can use real-time data to display in-store the harvest or pick date of a product, providing more accurate

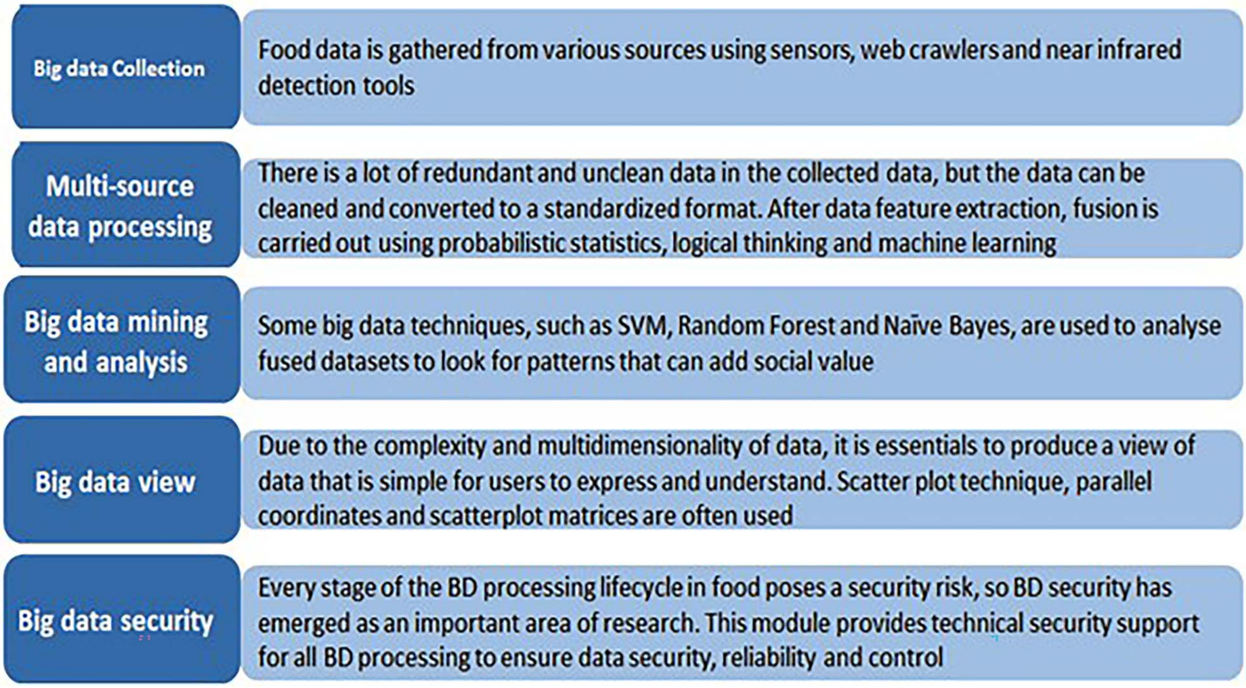

Figure 1. The processing system of the big data application in the food industry. Based on Tao et al. (2021).

information on sell-by, best-before, and use-by dates (Kayikci et al., 2022).

Zhu et al. (2022) determined the key environmental impacts that could result from the potential widespread application of the IoT in the food supply chain. A 20%–41% reduction in FLW was estimated, taking into account environmental costs. Smart shelves equipped with IoT-based sensors allow monitoring of how foods are handled and stored, by tracking the condition and the inventory of the items on the shelves Issues are identified by sensors and management is notified promptly to address them, preventing food wastage. Gull et al. (2021) devised a strategy to decrease FLW at home and in restaurants by using MQ4 and MQ135 sensors to detect gas emissions from various foods, including meat, rice, and bread. Jagtap et al. (2021) presented an IoT-based framework for monitoring the generation of FLW to improve resource efficiency in the food industry by designing and implementing IoT-based tools.

The food distribution industry is anticipated to be an early adopter of IoT technology, leading to improvements in the environmental and economic performance of the food supply chain performance (Heard et al., 2018; Nagarajan et al., 2022). For instance, autonomous vehicles enable in-home delivery, allowing customers to order smaller amounts of groceries for short-term needs. In shipping logistics, advancement in technology, particularly automation, can minimise FLW.

Artificial intelligence

AI plays a key role in the digital transformation of food supply chains and waste sorting to ensure sustainable food systems (Jamali & Misman, 2021; Marvin et al., 2022; Riesenegger et al., 2023). Inadequate market demand forecasting and supply chain management cause commercial food waste. AI is beneficial for demand forecasting, including customers, stores, distribution centres, manufacturers, ingredients, and raw material suppliers (Kumar et al., 2021). With AI-enabled software it is possible to make accurate forecasts by inputting previously recorded data on food stock-outs, discarded food, and real-time shelf-life and inventory data from the shelves (Şimşek, 2024). Using this type of software, stores can for example determine with enhanced precision when a particular food item will be out of supply, which in turn allows them to optimise their product ordering process and order quantities. Hassoun et al. (2022) demonstrated how AI could improve traceability, food processing, sensor-based data collection, and food safety. Figure 2 shows a general AI-based architecture for a FLW reduction system. Digital cameras or other sensors are the foundation for warehouses' FLW control systems.

FLW can also be reduced with an AI-powered food inspection system to evaluate food quality. Nagaraju and Shubhamangala (2020) used image processing and AI-based smart refrigerators to recognise food items and determine their freshness. Table 1 shows other examples of AI-based diagnosis technology used to assess food quality.

Human and machine intelligence working together can significantly reduce FLW. Machine learning (ML) helps to speed up circular design processes and prototypes by examining vast data sets and offering new possibilities and ideas for resource- and energy-efficient design (Akhtar et al., 2024). Leading corporations are already using ML to decrease FLW. For instance, Gupta et al. (2021) employed ML to estimate demand, resulting in a 20% decrease in prediction inaccuracy and a 30% reduction in lost revenue in a large food business. Nascimento et al. (2022) used AI to estimate small Brazilian grocery store demand and enable own-branded product production to prevent food waste using ML and feature expansion techniques. This approach generated the lowest amount of food waste and the largest gross profit. The suggested approach also decreased production costs while maintaining high demand.

Preventing and controlling plant disease outbreaks can also minimise early FLW during primary production (Aliyu et al., 2020; Velásquez et al., 2020). Sensors that monitor chemical and biological reactions on food products throughout the supply chain can be used to feed data into AI models. With this data, AI models can be

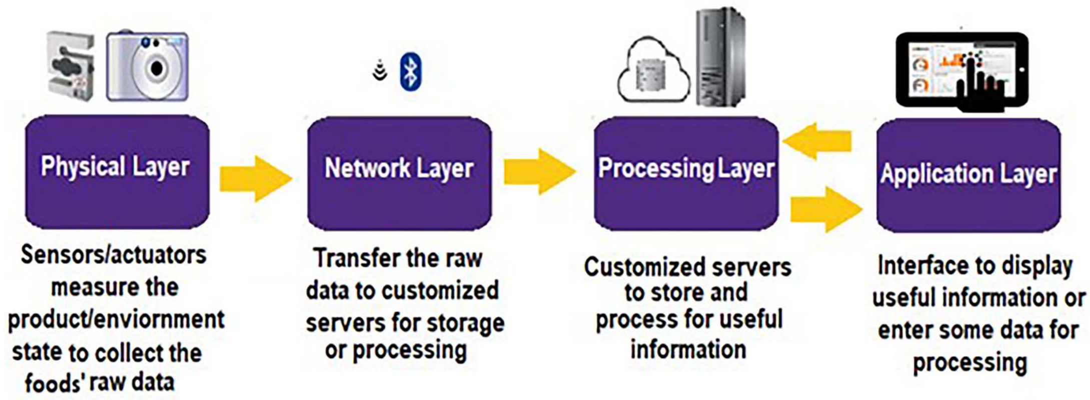

Figure 2. A general artificial intelligence architecture used for food loss and waste reduction.

Table 1. Early-stage artificial intelligence-based diagnosis technologies in assessing food quality.

Method	Objective	Findings	Reference
Hyperspectral imaging	Detect, classify, and quantify plant and animal-based adulterants in minced beef and pork	Classification rates of 75–100% for pure samples and 100% for adulterated samples	(Rady & Adedeji, 2020)
Mass spectrometry tested eight ML algorithms	Evaluate carcass quality	81.5% to 99% accuracy in predicting carcass quality traits	(Penning et al., 2020)
Support vector ML, stepwise, and Bayesian network procedures	Predict carcass traits and commercial meat cuts in lambs	Assess carcass traits or commercial cut predictions	(Alves et al., 2019)
Bilinear fusion method	Detect citrus greening disease	89% efficiency in detecting citrus greening disease	(Yang et al., 2021)
Control logic using an output feedback neural network	Maintain environmental conditions for proper plant growth	Identification and removal of infections	(Jung et al., 2020)

Note. ML = machine learning.

trained to detect infections so that the food items can be treated or removed from the supply chain. However, modelling plant disease detection requires a high-accuracy classification model. AI makes predicting crop yields, identifying weeds, and finding plant diseases easier (Shaikh et al., 2022). ML-based disease detection includes pre-processing the dataset, extracting the features of disease areas in the image using feature extraction algorithms, sending the feature information to the classifier to get the model parameters, and getting the disease categories and the level of disease to be detected (Ahmed & Yadav, 2023).

It is possible to develop a disease detection system for plants utilising a 3D convolutional neural network (CNN) model and hyperspectral images of leaves (Jung et al., 2020, 2022). Jagtap et al. (2019) described an automated and real-time system based on IoT that uses sophisticated image processing and load cell technologies to monitor the total quantity and the sources of FLW in the potato processing industry. A CNN was used to find the possible reasons for potato waste. A training accuracy of 94%, a validation accuracy of 86%, and a test accuracy of 83% were achieved after parameter optimisation. Mazloumian et al. (2020) used a deep CNN technique to categorise FLW into 20 distinct classifications with an accuracy of 83.5%. Anggraeni et al. (2021) used three AI implementations to support data analysis and decision-making on FLW. Algorithms for machine learning and Bayesian networks were used to estimate the amount of food wasted at the household level. An agent-based simulation was used to learn more about how innovation and the uptake of a certain technology might reduce retail food waste.

Thus, using AI techniques can increase the accuracy of production planning in the food processing industry and encourage a considerable decrease in FLW.

Blockchain

Blockchain technology stores digital information in a distributed and unalterable ledger, which fosters transparency and ultimately aids in preventing FLW. Food fraud is a major threat in the global food business, and food waste may be caused by food fraud (Visciano & Schirone, 2021). For instance, around 5,000 L of milk were destroyed by the District Food Authority of Pakistan due to the detection of adulterants and contaminants (Handford et al., 2016; Jha et al., 2016). Effective inventory control helps to restrict surplus food production, decrease overstocking, and enhance FLW management. For instance, the Raven Food Co-op has considerably reduced FLW by improving inventory control, selling discounted vegetables, and redistributing food to employees, co-op members, clients, and the local community (Ribeiro et al., 2019).

Many researchers have discussed how blockchain could raise awareness about FLW (Kayikci et al., 2022; Yiannas, 2018). They showed that using blockchain technology can facilitate consumers to verify the origin and safety of their food while enabling farmers to access vital information about market demand and pricing. All transactions are conducted online, and everyone has a ledger to keep track of exchanged tokens.

Kumar and Prashar (2021) used ML and blockchain to develop an autonomous warehouse system that reduces FLW. Dey et al. (2022) used blockchain, QR codes, cloud computing, and ML to build a framework that reduced FLW. Park and Li (2021) produced

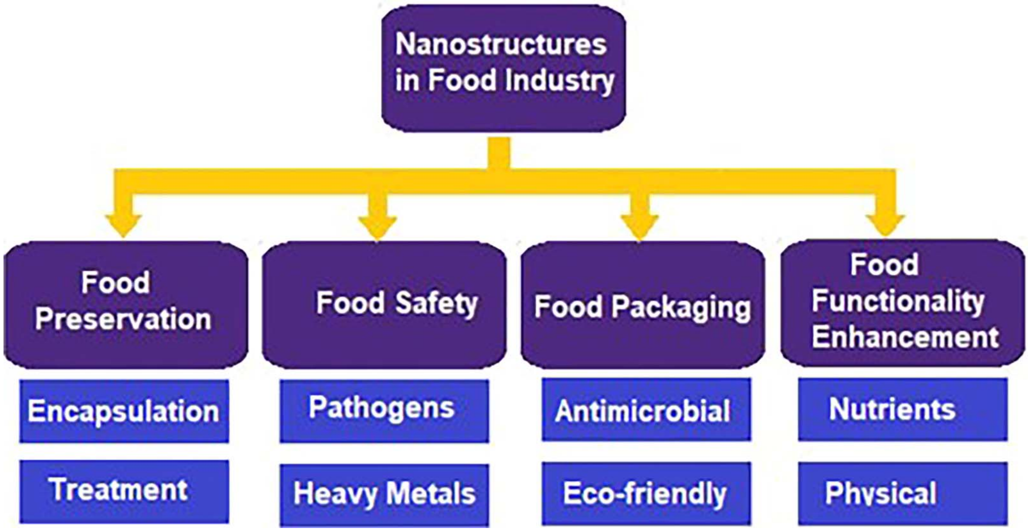

Figure 3. Applications of nanomaterials to protect food and reduce food loss and waste.

a case study demonstrating how supply networks might benefit from blockchain technology by examining the partnership between the Walmart food supply chain and IBM Food Trust. Before and after implementing the IBM Food Trust, they looked at Walmart's annual sustainability report and external ESG ratings. They demonstrated how the Walmart food supply chain benefits from blockchain technology regarding FLW control and food safety, health, and nutrition. These results showed that the blockchain can optimise FLW management and improve food safety, health, and nutrition in food supply chains.

Nanotechnology

Nanomaterials can be used in the food industry for a wide range of applications. Figure 3 illustrates how nanoparticles can be utilised in the food industry to safeguard food and reduce FLW. Recent advancements in nanotechnology in the food sector include improving safety and security, upgrading nutraceutical value, expanding shelf-life, and minimising FLW (Aguilar-Pérez et al., 2023; Ayala-Fuentes & Chavez-Santoscoy, 2021; He et al., 2019; Neme et al., 2021; Wesley et al., 2014).

Nanomaterials are extensively used to combat various pathogenic bacteria in food safety and preservation due to their superior physicochemical properties and antimicrobial potential (Baranwal et al., 2018, Das et al., 2018, Tian et al., 2022). (Thakur et al., 2018) identified a single *Escherichia coli* bacterial cell using a reduced graphene field-effect transistor device based on nanoparticles. Song et al. (2018) created a fluorescence sensing platform that employed immunomagnetic and liposome nanoparticles to detect *Cronobacter* sp. at the genus level with a 5.9×10^3 CFU/ml detection limit. Thus, nanotechnology can support FLW management by enhancing the accuracy and speed at which pathogenic bacteria, that cause food spoilage, can be detected. This in turn may lead to a reduction in costs and energy requirements of FLW prevention.

Smart packaging

The high perishability of food products has spurred the development of new packaging technologies to extend shelf life and enhance conservation. Solutions such as 'active packaging' use additives that interact with food or its environment to preserve, for example, fresh vegetables and animal products' freshness and shelf life. Intelligent, otherwise known as smart packaging technologies do not alter the food but monitor food quality throughout transportation and storage using sensor technology. Sensors can detect freshness, pH sensitivity (Zainal Arifin et al., 2023), food integrity, and ammonia sensitivity. They may also incorporate time–temperature indicators and RFID (Poyatos-Racionero et al., 2018). Zainal Arifin et al. (2023) demonstrated how intelligent packaging for meat and seafood products delayed lipid oxidation and slowed down microbiological development, maintaining food quality during storage and prolonging food shelf life. The qualitative information of these indicators changes over time and during processing due to chemical reactions or microbial growth. Bhargava et al. (2020) discussed different natural indicators made from FLW and recent research on the use of biodegradable smart packaging films with pigments derived from natural sources. The study aimed to assess whether the quality of food is maintained and to determine if there is commercial potential for these indicators.

Intelligent packaging, a subset of interactive packaging, is rapidly advancing. Although, most published information does not specifically mention the capabilities of intelligent packaging as a strategy for reducing FLW (Chen et al., 2020; Poyatos-Racionero et al., 2018). Numerous transduction mechanisms, including electrochemical (Chung & Dhar, 2021; Cruz Viggi et al., 2017; Habarakada Liyanage & Babel, 2020), electronic (Dos Santos et al., 2020; Raju et al., 2020), and mass-sensitive sensors are used to evaluate food quality (Li et al., 2022; Magarelli et al., 2023), which may help reducing FLW.

Cloud computing

A circular economy depends more on data and information than a linear economy. Figure 4 shows the communication models of different stakeholders in the food supply chain. Large volumes of data are generated from food supply chains, goods, materials, equipment, and manufacturing processes (Agrawal & Nyamful, 2016). Digital technology helps unleash the potential of certain circular methods by giving relevant information (Berg et al., 2020) This communication and monitoring model assists businesses in planning and ordering as required and reducing spoiling by providing complete visibility over product and ingredient expiration dates (Režek Jambrak et al., 2021). Industry 4.0 enables more

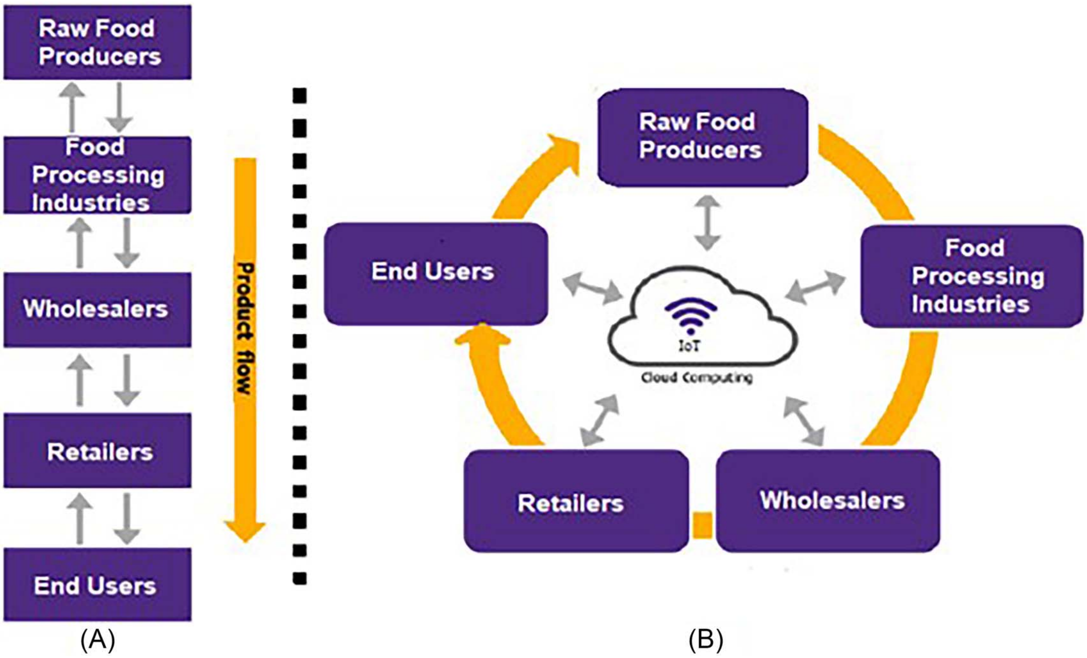

Figure 4. Communication channel in the food supply chain: (A) communication is limited to two stakeholders before Industry 4.0 and (B) communication is open to all stakeholders in Industry 4.0.

trustworthy communication between stakeholders than a linear model, where only stakeholders from adjacent levels typically communicate at each level.

Funchal et al. (2022) developed a digital cloud-based ecosystem to integrate smart applications in the food supply chain to reduce FLW. Benefits were obtained in terms of modularity, interoperability, scalability, and robustness. Further capabilities provided by cloud computing prevent FLW by streamlining order-to-delivery procedures.

3D food printing

3D food printing (3DFP) allows for the creation of highly sensitive, self-indicating, multipurpose smart components made from biocompatible, non-toxic materials at a lower cost than conventional manufacturing methods (Tracey et al., 2022). These technologies can be combined with intelligent food packaging to minimise food waste and shield people from ingesting unsafe food. Many studies have discussed the valorisation of FLW and its by-products using 3DFP (Carvajal-Mena et al., 2022; Cheng-Rong & Yung-Kai, 2022; Nida et al., 2022; Muthurajan et al., 2021; Wong et al., 2022).

Muthurajan et al. (2021) created ready-to-cook 3D-printed potato peel and wheat flour noodles. They found that tiny fractions of potato peel with particles less than 0.125 mm in size printed better than coarse fractions with particles larger than 0.125 mm because of the lower fibre content in fine fractions. Cheng-Rong and Yung-Kai (2022) investigated the production of an artificial steak to lessen the environmental damage caused by the meat industry. They found that gellan gum can compensate for proteins and regulate instrumental hardness and instrumental chewiness, which can be adjusted by various formulations and used in geriatric diets. (Carvajal-Mena et al., 2022) showed the potential of salmon gelatin gel for 3DFP, by efficiently exploiting gelatin gel from salmon skins to produce 3D-printed salmon gelatin cubes.

Additionally, 3DFP may aid in the optimisation of nutrition for certain target groups, such as athletes, the elderly and pregnant women, who might require soft diets or diets with special nutritional requirements (Pant et al., 2023). Režek Jambrak et al. (2021) discovered that 3DFP reduces carbon footprints, enables energy-efficient production, and requires minimal raw material use, making it a promising technology for sustainable foods.

Robotics and autonomous systems

The food industry has one of the lowest levels of automation. Despite enormous amounts of FLW being generated, this lack of automation has persisted because automation technologies face difficulties in contexts with such high variability and unpredictability as the food supply chain. However, the capacities of automation technologies are expanding, both cognitively and physically, and these restrictions are dwindling (Hassoun et al., 2022).

Researchers have investigated and developed robotics and autonomous systems (RAS) methods for fruit harvesting (Pearson et al., 2022). RAS harvesting for greenhouses has been developed, motivated by the fact that the manoeuvring of robots is easier within a closed environment such as a greenhouse (Sánchez-Molina et al., 2024). Jagtap et al. (2019) presented a RAS system for monitoring the quantity and source of potato waste throughout potato supply chains. The study demonstrates the utilisation of load cell technology and contemporary image processing to capture pictures of potatoes and weigh each of them separately.

Current barriers that hamper Industry 4.0 implementation in the food sector for FLW reduction

A thorough FLW reduction and management strategy requires numerous actions. However, owing to insufficient knowledge, poor coordination, and organisational issues, food service providers are mostly unaware of the advantages of radical innovations (Martin-Rios et al., 2018). There are still certain obstacles, such as control and security threats, inaccurate data, instability, and data biases. Economic risks (for example, decreased employment opportunities and high investment costs), unethical behaviour (in the case of intellectual property), and other social risks are still prevalent. The high investment costs make these solutions mostly applicable in developed economies and by highly profitable businesses. Regarding social risks, it is important to note that consumers may not understand some technology improvements, such as smart labels. It is therefore important that consumers are educated about the use of such technological advances, as well as to reduce food waste at the consumption level. The next level of Industry 4.0, i.e., Industry 5.0, adopts a more human-centric approach for digital technologies, and it is a recommended avenue of future research.

To promote policy alternatives that revitalise sustainable food systems, the interactions between digital technologies and FLW reduction require further investigation and in-depth research. Prohibitive investment prices and the digital gap among technology adopters constrain the widespread adoption of digital technologies.

Legislation poses a challenge in the food sector, as it varies geographically. The food industry produces a wide variety of goods, each with a unique production process and set of prerequisites for the supply chain. Therefore, the impact of digital technologies, especially those that generate data, depends critically on data sharing and integration, which is one of the biggest challenges faced by the food supply chain. From a data analytics perspective, data collection and transmission should be automated to the greatest extent. This is presently not the case since many businesses are not equipped with adequate data-gathering capabilities (Sevilla et al., 2022).

Furthermore, defining the required amount of data both in the present and in the future is challenging. The motivation to exchange data is also hampered by the different interests and conflicting goals of data owners. Ownership, confidentiality, and data management issues typically need to be settled through protracted discussions between data owners. When a large number of supply chain participants with competing interests are involved, reaching an agreement becomes very challenging (Kamilaris et al., 2019).

Conclusion

FLW reduction presents tremendous potential for all stakeholders in the food system to generate economic benefits while lowering environmental impacts. Efficient food systems benefit from advances in science, technology, public awareness, and demand for sustainable food. Industry 4.0 can support this transition to more sustainable food systems. Industry 4.0 comprises technologies that boost production, improve food safety, minimise FLW, reduce resource use, and enable total supply chain transparency from farm to fork. It allows corporations to collect detailed data from sensors placed across the entire food system and analyse it to streamline their decision-making processes. Several Industry 4.0 technologies substantially enhance the human ability to make more accurate decisions. As a result of precision forecasting and the right conditions for processing, FLW can be significantly reduced. Industry 4.0 technologies can enable continuous feedback loops between the various phases of the food production process and improve trust, traceability, and transparency throughout the entire value chain, further improving data sharing and accessibility. Consequently, improved communication and access to data allows for optimisation of food operations and reduction of FLW. Therefore, Industry 4.0 offers many possibilities to minimise FLW and optimise the efficiency of the food sector. Nevertheless, its implementation is currently limited due to restrictive regulations, lack of market demand, technological awareness, and the need for large investments.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Author contributions

Rai Naveed Arshad (Conceptualisation [equal], Formal analysis [equal], Investigation [equal], Methodology [equal], Validation [equal], Writing—original draft [equal]), Zulkurnain Abdul-Malek (Conceptualisation [equal], Formal analysis [equal], Investigation [equal], Methodology [equal], Writing—original draft [equal]), Carlos Parra López (Data curation [equal], Formal analysis [equal], Investigation [equal], Methodology [equal], Validation [equal], Writing—original draft [equal]), Abdo Hassoun (Conceptualisation [equal], Data curation [equal], Formal analysis [equal], Investigation [equal], Methodology [equal], Validation [equal], Visualisation [equal], Writing—original draft [equal]), Muhammad Imran Qureshi (Conceptualisation [equal], Formal analysis [equal], Investigation [equal], Writing—original draft [equal]), Aysha Sultan (Data curation [equal], Formal analysis [equal], Investigation [equal], Validation [equal], Writing—original draft [equal]), Carmen Carmona-Torres (Validation [equal], Writing—review & editing [equal]), Jennifer Mignonne de Waal (Data curation [equal], Formal analysis [equal], Investigation [equal], Writing—review & editing [equal]), Sandeep Jagtap (Formal analysis [equal], Funding acquisition [equal], Investigation [equal], Project administration [equal], Resources [equal], Supervision [equal], Writing—review & editing [equal]), and Guillermo Garcia-Garcia (Data curation [equal], Funding acquisition [equal], Project administration [equal], Software [equal], Supervision [equal], Validation [equal], Writing—review & editing [equal])

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Conflicts of interest

Authors state that there is no conflict of interest.

Ethical approval

Ethics approval was not required for this research.

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