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Artificial Intelligence and Internet of Things in Food Supply Chain Sustainability: A Data-Driven Approach to Waste Reduction, Predictive Quality Management, and Circular Economy Integration

Ebrahim Alinia-Ahandani[1]*, Alireza Saeidgohari[1], Zahra Alizadeh-Tarpoei[2], Alireza Mehregan Nikoo[3], Sahebe Hajipour[4], Hossein Fathi[5], Batuhan Selamoglu[6,7]

1-Food and Drug Research Center, Food and Drug Administration, Military of Health and Medical Education, Tehran, Iran. https://orcid.org/0000-0002-1633-086X
2-Department of Plant Biology, faculty of Basic Sciences, University of Guilan, Rasht, Iran
3-Department of Food Sciences and Technology, Faculty of Agriculture, University of guilan, Rasht, Iran. https://orcid.org/0000-0002-9377-9441
4-Department of Biology, Faculty of Sciences, Golestan University, Gorgan, Iran. https://orcid.org/0000-0001-5895-7620
5-Deputy of Food and Drug, Guilan University of Medical Sciences, Rasht, Iran
6-Department of Electronics Technology, Istanbul Arel University, Istanbul, Türkiye
7-Department of Electrical and Electronics Engineering, Institute of Life Sciences, Mersin University, Mersin, Türkiye
E-Mail: batuhanselamoglu@arel.edu.tr, ORCID ID: 0000-0003-0634-1589
**Corresponding Author's E-Mail: dr.ebrahim.alinia@gmail.com*

Abstract

Food loss and waste (FLW) represent one of the most paradoxical failures of the modern food system: roughly one-third of all food produced for human consumption – approximately 1.3 billion tonnes annually – is lost or wasted, while 828 million people face chronic hunger. This review provides a comprehensive and critical synthesis of how Artificial Intelligence (AI) and Internet of Things (IoT) technologies are being deployed across the food supply chain (FSC) to monitor, predict, and reduce FLW. We systematically evaluate 85 peer-reviewed studies (2020–2026) covering the entire chain from primary production to retail and consumer behaviour. Specific applications include: (i) AI-powered yield prediction and precision harvesting in agriculture; (ii) IoT-based cold chain monitoring with real-time quality degradation modelling; (iii) computer vision for dynamic expiry date prediction and automated sorting in food processing; (iv) AI-driven demand forecasting and inventory optimisation in retail; and (v) consumer-facing smart storage and digital nudging. We critically examine the technical barriers – sensor cost, data interoperability, model generalisation across food types – as well as organisational and behavioural challenges. Integration of nanotechnology-based sensors (e.g., for ethylene or volatile amines) with IoT platforms is highlighted as an emerging frontier. Life cycle assessment (LCA) of AI/IoT interventions shows that FLW reduction of 25–40% is achievable, with corresponding decreases in GHG emissions, water use, and land pressure. Finally, we discuss the role of circular economy principles and the need for open data standards. Our conclusion is that AI and IoT are no longer optional but essential for a resilient, low-waste food system, provided that implementation costs are addressed and data governance frameworks are established.

Keywords: *Artificial intelligence, Internet of Things, food waste reduction, cold chain monitoring, predictive quality, circular economy, nanotechnology sensors, smart agriculture, demand forecasting*

1. Introduction

The scale of global food loss and waste is staggering, yet it has become so routine that most supply chain actors accept it as inevitable. According to the Food and Agriculture Organization (FAO), approximately 14% of food produced globally is lost between harvest and retail, and an additional 17% is wasted at the retail, food service, and household levels [1]. Combined, this represents about 1.3 billion tonnes per year, with an estimated economic value of nearly one trillion US dollars. The environmental cost is equally severe: FLW accounts for 8–10% of total anthropogenic greenhouse gas (GHG) emissions – roughly three times the emissions from global aviation [2]. Moreover, wasted food consumes about 250 km³ of fresh water annually (equivalent to the annual flow of the Volga River) and occupies 1.4 billion hectares of land, nearly 30% of the world's agricultural land area [3].

Paradoxically, FLW occurs unevenly across the supply chain. In low-income countries, losses are concentrated at the early stages – harvest, drying, storage, and transport – due to inadequate infrastructure, lack of refrigeration, and pest infestation. In high-income countries, waste dominates at the consumer level (households and food service), driven by aesthetic standards, oversized portions, confusion about date labels, and suboptimal storage behaviour [4]. In middle-income nations, both upstream losses and downstream waste are significant, creating a complex challenge that cannot be solved by any single intervention.

Traditional approaches to FLW reduction have focused on logistics improvements (better roads, cold storage), packaging innovations (modified atmosphere), and consumer education campaigns. While valuable, these strategies are often reactive and static – they do not adapt to real-time variations in product condition, demand fluctuations, or environmental factors. Over the past five years, a new paradigm has emerged: the integration of **Artificial Intelligence (AI)** and **Internet of Things (IoT)** to create a dynamic, data-driven food supply chain (FSC) [5]. In this paradigm, low-cost sensors (temperature, humidity, ethylene, vibration) generate continuous streams of data about food condition; these data are transmitted via wireless networks to cloud or edge platforms; and AI models – including machine learning, deep learning, and reinforcement learning – analyse the data to predict spoilage kinetics, optimise routing, adjust storage parameters, and even recommend dynamic pricing for soon-to-expire products.

The potential impact is substantial. A systematic review by the World Resources Institute (WRI) estimated that widespread adoption of AI/IoT solutions could reduce FLW by 25–40% across high-value supply chains (perishables, dairy, meat, seafood) [6]. Early case studies show impressive results: a large European retailer used a recurrent neural network (RNN) to forecast store-level demand for fresh produce, reducing waste by 30% while maintaining 98% product availability [7]. A cold-chain logistics company integrated IoT sensors with a digital twin model, enabling dynamic rerouting of shipments to avoid delays; this reduced spoilage of fresh berries by 22% [8].

Nevertheless, implementation is not trivial. Sensor hardware must be affordable, robust, and food-contact safe. Data interoperability across different supply chain actors (farmers, logistics providers, retailers) remains poor. AI models trained on one food product (e.g., strawberries) often fail to generalise to another (e.g., leafy greens) because spoilage mechanisms differ. Furthermore, the energy consumption of continuous IoT monitoring and cloud processing must itself be considered in life cycle assessments – a point often overlooked.

This review has four main objectives. First, to systematically map the application of AI and IoT across each stage of the FSC, from primary production to consumer behaviour. Second, to critically assess the technical and economic performance of these systems based on published data. Third, to highlight emerging technologies – particularly nanotechnology-based gas sensors that can detect spoilage volatiles (ethylene, ammonia, biogenic amines) at parts-per-billion levels – that can be integrated with IoT platforms [9–11]. Fourth, to discuss the barriers to adoption and propose a research agenda. Throughout, we also draw attention to the quality and safety of raw agricultural materials – including contamination by heavy metals, pesticide residues, and mycotoxins – because sensor systems designed for waste reduction can simultaneously monitor for these hazards, as shown in recent studies from Iran and elsewhere [12–18]. By integrating food safety and waste reduction, the value proposition of AI/IoT becomes even stronger.

2. Materials and Methods

2.1 Search Strategy

A systematic search was conducted following PRISMA guidelines [19]. Databases: Scopus, Web of Science, IEEE Xplore, PubMed, and Google Scholar. Search period: January 2020 to March 2026. Search strings combined terms:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "predictive analytics") AND
("Internet of Things" OR "IoT" OR "wireless sensor network" OR "RFID" OR "smart sensor") AND
("food waste" OR "food loss" OR "perishable" OR "shelf life" OR "spoilage" OR "cold chain" OR "supply chain") AND
("agriculture" OR "harvest" OR "logistics" OR "retail" OR "consumer").

For nanotechnology-sensor integration, we added: ("nanosensor" OR "biosensor" OR "ethylene sensor" OR "volatile organic compound" OR "biogenic amine") AND ("IoT" OR "wireless").

2.2 Inclusion and Exclusion Criteria

Inclusion: (i) peer-reviewed original research or reviews in English; (ii) reporting quantitative outcomes (e.g., % waste reduction, prediction accuracy, cost savings); (iii) field-tested or validated with real data (not purely simulation); (iv) for sensor papers: detection limit and response time reported. Exclusion: purely theoretical studies without data; studies on non-food waste (e.g., municipal solid waste); conference abstracts without sufficient detail.

2.3 Data Extraction

Extracted parameters: supply chain stage, food commodity, sensor type (temperature, humidity, gas, motion), communication protocol (Wi-Fi, LoRaWAN, NB-IoT, 5G), AI/ML algorithm (random forest, XGBoost, LSTM, CNN, etc.), sample size, prediction accuracy (R^2, RMSE, F1-score), reported waste reduction (%), implementation cost (USD), and payback period (months). For nano-sensors: target analyte, detection limit (ppb/ppm), response time (seconds), and integration method.

2.4 Quality Assessment

Studies were assessed using an adapted version of the QUADAS-2 tool for predictive models and a custom scoring system for IoT field deployments. LCA studies were evaluated against ISO 14040/14044 criteria.

3. Results

3.1 AI/IoT Applications Across the Food Supply Chain

We identified 85 studies that met inclusion criteria. The distribution across supply chain stages is shown in **Table 1** .

Stage	*Number of studies*	*Typical technologies*	*Reported waste reduction*	*Key challenges*
Primary production (pre-harvest & harvest)	22	Satellite/Drone imagery + CNNs, soil IoT sensors, yield prediction models	15–25% (reduced premature harvest losses)	Model transferability across climates
Post-harvest storage & transport (cold chain)	30	Wireless T/H sensors, ethylene nanosensors, LSTM spoilage prediction, digital twins	20–35%	Sensor cost; power supply; data gaps
Food processing & packaging	12	Computer vision for dynamic expiry labelling, IoT-enabled smart packaging (TTI)	10–20%	Integration with existing lines
Retail (supermarkets, food service)	15	AI demand forecasting (XGBoost, RNN), dynamic pricing, smart shelves	25–40%	Data silos between suppliers and retailers
Household consumption	6	Smart fridges with inventory tracking, camera-based waste logging, digital nudging apps	10–30%	User engagement; privacy

3.2 Cold Chain Monitoring: The Largest Opportunity

The cold chain – from farm to retail refrigerated display – is where most perishable food waste occurs (estimated 25% of fresh produce, 20% of dairy, 35% of seafood) [20]. Thirty studies focused on IoT-enabled cold chain monitoring. The most robust findings are:

- **Wireless sensor networks (WSN)**: Low-power temperature/humidity sensors (e.g., DHT22, SHT30) combined with LoRaWAN or NB-IoT provide continuous monitoring with battery life >6 months. In a field test across 12 refrigerated trucks carrying strawberries, real-time alerts for temperature excursions (>4°C for >2 hours) reduced spoilage from 18% to 6% [21].
- **Predictive quality models**: Using historical time-series of temperature and vibration, Long Short-Term Memory (LSTM) networks predict remaining shelf life with an error of ±0.8 days (compared to traditional kinetic models which have ±2.3 days error) [22]. A study on fresh Atlantic salmon used an LSTM with IoT inputs (T, humidity, gas – trimethylamine) achieved $R^2 = 0.93$ for spoilage prediction [23].
- **Digital twins**: A digital twin of a cold storage facility – which mirrors the real-time physical state – allows operators to simulate “what if” scenarios (e.g., door opening frequency, compressor failure). One cold storage operator reduced energy use by 18% while reducing spoilage by 12% using this approach [24].

3.3 AI for Demand Forecasting and Retail Waste Reduction

Retail waste is driven primarily by mismatches between supply (often based on historical averages) and variable demand (weather, promotions, holidays, local events). Machine learning models that incorporate multiple data streams – point-of-sale (POS) data, weather forecasts, calendar features, even social media sentiment – have become highly accurate. In a meta-analysis of 15 retail studies, the weighted average waste reduction was **32%** for fresh produce, 28% for bakery, and 19% for dairy [25].

The best performing algorithm was a gradient-boosted ensemble (XGBoost + LightGBM) that achieved a mean absolute percentage error (MAPE) of 12% for daily store-item demand, compared to 28% for traditional moving averages [26]. A large UK supermarket chain implemented such a system across 500 stores: waste fell by 25% within one year, and out-of-stock events decreased by 15% [27]. Importantly, the system also enabled **dynamic pricing** – automatically discounting items approaching their use-by date – which shifted 35% of otherwise wasted products to sold at reduced margin but positive contribution.

3.4 Emerging Sensor Technologies: Nanosensors and Biosensors

Traditional temperature and humidity sensors are insufficient for many fresh foods because spoilage is driven by biochemical changes (e.g., ethylene production in climacteric fruits, biogenic amine accumulation in fish). Nanotechnology has enabled a new generation of highly sensitive, low-cost gas sensors that can be integrated directly into IoT platforms [9,10]. Key examples:

- **Ethylene nanosensors** for fruit ripening monitoring: Carbon nanotube-based chemiresistors detect ethylene down to 10 ppb. When integrated with a wireless transmitter and placed inside a fruit container, the system alerts the operator when ethylene exceeds a threshold (e.g., 50 ppb for bananas), triggering ventilation or removal of ripening fruit [28]. Field tests on banana shipments reduced over-ripening waste by 40% [29].
- **Ammonia and biogenic amine sensors** for fish and meat: Polyaniline- or metal oxide-based nanosensors respond to trimethylamine (TMA) and cadaverine – key spoilage markers. A recent study demonstrated a flexible, printed nanosensor array that attaches to the inner surface of packaged fish fillets. Data transmitted via NFC to a smartphone can calculate remaining shelf life with 89% accuracy [30].
- **Heavy metal and pesticide detection**: While not directly for waste reduction, the same IoT infrastructure can be used to monitor contaminants. As reported in multiple studies from Iran and other regions, raw agricultural materials (medicinal plants, rice, vegetables) sometimes contain elevated levels of lead, cadmium, or arsenic due to soil pollution [12–18]. Nanosensors functionalised with specific chelators can detect these metals at ppb levels. Integrating such sensors into receiving docks could enable real-time

rejection of contaminated batches, preventing both waste (if rejected early) and health risks. Hajipour et al. (2023) reviewed the application of nanoparticles in phytoremediation and sensing, highlighting the dual benefit of remediation and detection [17]. Alinia-Ahandani & Hajipour (2026) provided a broader perspective on nanotechnologies for removal of polycyclic aromatic hydrocarbons (PAHs) from smoked rice, which can be adapted for sensor development [18].

3.5 Life Cycle Assessment and Economic Viability

Five LCA studies examined the net environmental impact of deploying AI/IoT for FLW reduction [31–35]. The key finding is that the **embodied emissions** of sensors, communication infrastructure, and cloud computing are small (typically <2% of the emissions from the wasted food that is saved). For example, a system of 1,000 IoT temperature loggers distributed across a cold chain (each with a 5-year lifespan) has an embedded carbon footprint of approximately 0.5 tonnes CO_2-eq, while the food waste it prevents over the same period avoids 50–100 tonnes CO_2-eq [31]. Thus, even with conservative assumptions, the net benefit is strongly positive.

Economic payback periods vary. For high-value perishables (berries, seafood, cut flowers), payback is often less than 6 months. For lower-value commodities (potatoes, onions), payback can exceed 2 years, which may deter investment without subsidies [32]. The cost of nanosensors remains higher than conventional T/H sensors – approximately \$5–15 per unit compared to \$1–3 – but prices are falling rapidly with printed electronics.

4. Discussion

The evidence assembled in this review indicates that AI and IoT technologies are not speculative future solutions but operational tools that are already delivering measurable reductions in food waste across real supply chains. However, several critical barriers must be overcome to achieve widespread adoption, particularly in low- and middle-income countries where losses are highest.

Technical barrier – model generalisation: Most AI models are trained on specific food varieties, packaging types, and environmental conditions. An LSTM trained on cv. 'Cavendish' bananas from Ecuador may perform poorly on cv. 'Grand Naine' from the Philippines due to different respiration rates. Transfer learning and domain adaptation techniques are being developed, but they require sharing data across supply chain partners – which is often commercially sensitive. Federated learning, where models are trained locally and only parameter updates are shared, offers a promising path [36].

Data interoperability and standards: Currently, sensor data formats, communication protocols, and cloud platforms are highly fragmented. A farmer using a LoRaWAN network cannot easily share data with a logistics provider using a 5G-based system unless both adopt a common data schema (e.g., GS1's Electronic Product Code Information Services – EPCIS). The development of open standards for food IoT data is urgently needed, and organisations like the Open Food Chain Association (OFCA) are working in this direction [37].

Cost and energy in low-resource settings: In many low-income countries, the capital cost of IoT sensors (even low-cost ones) remains prohibitive for smallholder farmers. Innovative business models – such as "sensor-as-a-service" where farmers pay a small subscription fee – have shown promise in pilot projects in Kenya and Bangladesh [38]. Additionally, low-power wide-area networks (LPWAN) like LoRaWAN can operate for years on a single battery, and solar-powered gateways eliminate grid dependence.

Integration of food safety monitoring: A significant opportunity is to combine FLW monitoring with food safety surveillance. The same IoT platforms that track temperature and humidity can also host sensors for heavy metals, mycotoxins (aflatoxin, ochratoxin), and pesticide residues. As noted in the Iranian studies referenced earlier, contamination of medicinal plants, rice, and animal products with lead, cadmium, and other toxic elements remains a concern [12–15,17]. Alinia-Ahandani et al. (2022) systematically reviewed the safety evaluation of toxic elements in medicinal plants, emphasising that routine monitoring is insufficient in many regions [15]. If IoT-enabled nanosensors for these contaminants become affordable, they could serve a dual purpose: rejecting contaminated batches (preventing health risks) and also reducing waste by directing less-contaminated materials to appropriate uses (e.g., processing rather than raw consumption).

Behavioural aspects – the consumer link: Even the most sophisticated AI/IoT system cannot force a household to eat food before it spoils. However, digital nudging – using notifications, recipe suggestions, and visual feedback – has been shown to reduce household waste by 15–20% [39]. A smart fridge that tracks inventory and displays a "use by tonight" list on a smartphone app reduced self-reported waste by 28% in a six-month Swiss study [40]. Privacy concerns remain; many users are uncomfortable with cameras inside their fridge. Simpler solutions (RFID tags on grocery items paired with a door sensor) achieve similar benefits with less intrusion.

Environmental trade-offs: While LCA generally supports AI/IoT for FLW reduction, there are edge cases where the sensors themselves have high embodied energy (e.g., short-lived, non-recyclable sensors using rare earth metals). The electronics waste (e-waste) from discarded sensors is a growing concern. Designing sensors with biodegradable substrates (cellulose, polylactic acid) and using additive manufacturing (inkjet printing of silver nanoparticles) can reduce both cost and environmental footprint [41].

Future directions: We foresee five transformative developments over the next decade: (i) **ubiquitous low-cost nanosensors** – printed gas sensors below \$0.10 per unit, enabling every package to have a "digital freshness indicator"; (ii) **AI-powered dynamic shelf life** – models that continuously update use-by dates based on actual time-temperature history rather than static labels; (iii) **autonomous cold chain vehicles** – delivery drones and autonomous trucks that use real-time spoilage data to reroute to the nearest market; (iv) **blockchain integration** – immutable records of food condition for insurance claims and liability; (v) **regulatory mandates** – governments requiring IoT monitoring for high-risk perishables, similar to the EU's cold chain regulations for pharmaceuticals.

5. Conclusions

Food loss and waste is not an inevitable cost of doing business – it is a solvable problem. The convergence of low-cost IoT sensors, advanced machine learning, and cloud computing has created an unprecedented opportunity to monitor, predict, and mitigate waste across the entire food supply chain. This review has shown that:

- In primary production, AI-driven yield prediction and precision harvesting can reduce pre-harvest losses by 15–25%.
- In cold chain logistics, IoT-based real-time monitoring combined with LSTM spoilage models reduces waste by 20–35%, with digital twins offering additional efficiency gains.
- In retail, AI demand forecasting and dynamic pricing cut waste by 25–40%, while also improving product availability.
- Emerging nanosensor technologies (ethylene, biogenic amines, heavy metals) can be integrated with IoT platforms to provide real-time quality and safety data, addressing both waste and contamination risks – a dual benefit highlighted by recent research on toxic elements in food raw materials [12–18].

The economic and environmental returns on investment are strongly positive for high-value perishables, though lower-value commodities may require subsidy or shared infrastructure. Key barriers – cost in low-income settings, data interoperability, model generalisation, and consumer behaviour change – are being addressed through technical innovation, open standards, and behavioural science.

For the international food industry, the message is clear: AI and IoT are no longer optional enhancements but essential components of a resilient, low-waste, and safe food system. Policymakers should support the development of open data standards, invest in digital infrastructure for cold chains, and encourage the adoption of smart sensors through tax incentives or mandates for high-risk products. Researchers should focus on low-cost, biodegradable sensor platforms, transfer learning methods that work across diverse food types, and integration of food safety surveillance into waste reduction systems.

Finally, it is worth remembering that every tonne of food waste prevented avoids not only economic loss but also unnecessary GHG emissions, water consumption, and land use. In a world of finite resources, making our food supply chain intelligent is not just good business – it is a moral imperative.

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