CHAPTER 16

MULTISENSORY IOT SYSTEMS FOR FOOD QUALITY AND SAFETY MONITORING IN THE CONTEXT OF ESG AND INDUSTRY 4.0

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INTRODUCTION

The global food industry is experiencing a profound transformation driven by the convergence of digital technologies, shifting regulatory landscapes, and evolving consumer expectations. The fourth industrial revolution (Industry 4.0) has introduced a new paradigm of connected, data-driven production in which physical processes are continuously monitored, analyzed, and optimized through cyber-physical systems. In the food sector, this transformation is particularly consequential: food safety failures have direct implications for public health, and the economic costs of product recalls, foodborne illness outbreaks, and supply chain disruptions run into billions of dollars annually worldwide[1].

According to the Food and Agriculture Organization of the United Nations (FAO), approximately 1.3 billion tonnes of food – or about one-third of all food produced globally – is lost or wasted each year[2]. A substantial portion of these losses occurs due to inadequate monitoring of temperature, humidity, and other critical parameters during storage and transportation. The cold chain, which encompasses the entire low-temperature logistics pathway from farm to consumer, remains one of the most vulnerable segments of the food supply system. Reactive, manual monitoring methods are increasingly inadequate to address the scale, complexity, and speed of modern food distribution networks.

Simultaneously, the principles of Environmental, Social, and Governance (ESG) accountability have evolved from voluntary frameworks into binding regulatory requirements in the European Union and beyond. The EU Corporate Sustainability Due Diligence Directive (CSDDD), the Sustainability-related

[1] Muller W. A., Ferreira S. B., da Silva S. B. Enhancing Food Safety in the Cold Chain Through Internet of Things and Artificial Intelligence. Journal of Food Science. 2026. https://doi.org/10.1111/1750-3841.70871.

[2] FAO. Food Loss and Waste Database. URL: https://www.fao.org/platform-food-loss-waste (accessed: 10.05.2026).

Financial Disclosures Regulation (SFDR), and the Green Deal Action Plan collectively establish stringent obligations for food companies to measure, document, and disclose their environmental and social impacts[3]. Empirical research on European food sector companies confirms a positive and statistically significant relationship between investment in digital transformation, ESG compliance, and firm-level financial performance[4]. This creates a powerful business case for deploying IoT-based monitoring infrastructure not merely as a compliance tool, but as a source of competitive advantage.

At the intersection of these two trends – digital transformation and ESG imperatives – stand multisensor embedded systems: specialized computer systems integrating arrays of diverse physical and chemical sensors with onboard processing, wireless communication, and cloud connectivity. These systems enable continuous, real-time acquisition of food quality parameters across the entire production and supply chain lifecycle. When combined with edge computing architectures and machine learning algorithms, multisensor IoT platforms can detect quality deviations and predict spoilage hours before conventional methods would identify a problem, enabling proactive intervention and dramatically reducing waste[5].

The rapid development of low-power microcontrollers such as the ESP32-S3, STM32WB series, and Nordic nRF52840, alongside advances in miniaturized chemical and optical sensors, has made sophisticated multisensor nodes increasingly affordable and energy-efficient. The emergence of TinyML – the deployment of machine learning inference on resource-constrained microcontrollers – further extends the intelligence frontier to the very edge of the IoT network, enabling autonomous decision-making without reliance on cloud connectivity[6]. These technological developments are rapidly moving IoT-based food monitoring from research prototypes to scalable industrial deployments.

The purpose of this chapter is to provide a comprehensive analysis of the architecture, sensor technologies, data fusion methodologies, and ESG implications of multisensor IoT systems for food quality and safety monitoring. Section 1 examines the multilayer architectural design of such systems, with

[3] Fortude. Sustainable Digital Transformation for F&B. 2026. URL: https://fortude.co/blog/why-sustainable-digital-transformation-is-non-negotiable-for-food-and-beverage-fb-businesses-in-2025-26 (accessed: 14.05.2026).

[4] Marczewska M. et al. Digital transformation, ESG, and companies performance in the European food sector. *Journal of Technology Transfer*. 2025. https://doi.org/10.1007/s10961-025-10247-1.

[5] Plakantara S. P., Karakitsiou A. The future of digital innovation in transforming food safety systems. *npj Science of Food*. 2026. https://doi.org/10.1038/s41538-026-00809-4.

[6] Sensor technologies in the food industry under industry 4.0. Food Control. 2026. https://doi.org/10.1016/j.foodcont.2026.002288.

particular attention to edge and cloud computing paradigms and hardware platforms. Section 2 reviews the principal sensor modalities employed in food monitoring and the signal processing and fusion algorithms that transform raw sensor data into actionable quality indicators. Section 3 analyzes the role of IoT monitoring systems as an enabling infrastructure for implementing ESG strategies across environmental, social, and governance dimensions.

1. Architecture of multisensor IoT systems for the food industry

Modern IoT systems for food industry applications are designed around a multilayer architecture encompassing four principal strata: the perception layer, the network layer, the processing layer, and the application layer. This hierarchical design separates concerns, optimizes resource utilization at each tier, and provides the modularity necessary for scalable deployment across heterogeneous production and logistics environments. Understanding the function and interaction of each layer is essential for engineering reliable, high-performance food monitoring solutions.[7]

At the perception layer, multisensor nodes – specialized embedded systems equipped with arrays of physical and chemical transducers – capture a continuous stream of environmental and product-state data. Typical measurements include temperature (NTC thermistors, PT100/PT1000 RTDs), relative humidity (capacitive polymer sensors), atmospheric pressure, pH (glass electrode or solid-state ISFET sensors), dissolved oxygen, CO2, ethylene, and volatile organic compound (VOC) concentrations measured via metal oxide semiconductor (MOS) or electrochemical gas sensors. The hallmark capability of such nodes is sensor fusion: the concurrent acquisition and integration of signals from multiple heterogeneous transducers to produce a composite, higher-confidence estimate of the product quality state that is unattainable from any single sensing modality[8].

The hardware platform of sensor nodes typically centers on a low-power system-on-chip (SoC) integrating a 32-bit processor core, multi-channel analog-to-digital converters (ADC), digital communication interfaces (I2C, SPI, UART), and an IEEE 802.15.4 or Bluetooth Low Energy (BLE) radio transceiver. Prominent platforms include the Espressif ESP32-S3 (dual-core Xtensa LX7, integrated Wi-Fi/BLE), STMicroelectronics STM32WB55 (Arm Cortex-M4/M0+ with BLE 5.4), Nordic Semiconductor nRF52840 (Arm Cortex-M4, Bluetooth 5.0/Thread/Zigbee), and the u-blox SARA-R4 series for

[7] IEEE. Application Areas of Industry 4.0 Technologies in Food Manufacturing. 2019. https://doi.org/10.1109/IEEM.2018.8711184.

[8] IoT-Based Food Quality Monitoring System. Scribd. 2025. URL: https://www.scribd.com/document/878788761 (accessed: 14.05.2026).

cellular NB-IoT connectivity. The architecture of these devices – integrating computation, sensing interfaces, and radio in a single package – represents a textbook example of specialized computer systems optimized for the tight power and footprint constraints of industrial IoT deployments[9].

The network layer provides the communication infrastructure connecting distributed sensor nodes to processing resources. Protocol selection is governed by a multi-dimensional trade-off among power consumption, communication range, data throughput, and latency. Short-range protocols (Zigbee, Thread, BLE Mesh, Z-Wave) are suited for dense in-facility deployments; Wi-Fi 6 (IEEE 802.11ax) supports higher-bandwidth applications such as video inspection systems; while LPWAN standards – LoRaWAN (operating at 868 MHz in Europe, up to 15 km range) and NB-IoT (3GPP Release 13) – are preferred for wide-area cold-chain tracking, where sensor nodes must transmit infrequent, low-volume data over long distances with battery lifetimes measured in years[10].

Edge computing occupies the critical intermediate tier between raw data acquisition and centralized cloud analytics. Edge gateways – industrial-grade single-board computers or PLC-class controllers collocated with sensing infrastructure – perform real-time signal filtering, feature extraction, anomaly detection, and local alarming without incurring the latency and bandwidth costs of cloud round-trips. In food production contexts, edge processing enables sub-second detection of critical control point (CCP) violations as mandated by HACCP frameworks, ensuring corrective action can be initiated within the response window required by food safety regulations11. Studies on industrial edge computing confirm that local analytics can reduce manufacturing losses attributable to delayed response by up to 40% relative to cloud-only architectures.

At the application layer, aggregated and contextualized data are integrated with enterprise systems, including Quality Management Systems (QMS), Enterprise Resource Planning (ERP) platforms, and regulatory compliance databases. Modern implementations adhere to global interoperability standards: GS1 Digital Link and EPCIS 2.0 (Electronic Product Code Information Services) provide a standardized, event-based data model for end-to-end product traceability consistent with ISO 22000, the US Food Safety Modernization Act (FSMA), and GFSI-recognized certification schemes (BRC, SQF, FSSC

[9] Sensor technologies in the food industry under industry 4.0. Food Control. 2026. https://doi.org/10.1016/j.foodcont.2026.002288.

[10] ANKO Food Machine. AI and IoT innovations improve food production efficiency. 2024. URL: https://www.anko.com.tw/uk/news/Press-smart-food-manufacturing-IoT-technology.html (accessed: 14.05.2026).

[11] WorldBakers. Step by Step to Digital Food Safety. 2024. URL: https://www.worldbakers.com/step-by-step-to-digital-food-safety (accessed: 14.05.2026).

22000). API-driven integration enables IoT data streams to trigger automated workflow actions – such as quarantine orders, supplier notifications, and logistics re-routing – transforming passive monitoring into an active, self-correcting supply chain management capability[12].

2. Sensor modalities and data fusion methods in food quality monitoring systems

The sensor base of IoT-enabled food monitoring systems spans an expanding portfolio of transducer technologies, each sensitive to distinct physicochemical properties relevant to food quality and safety. The scientific literature distinguishes five principal sensor classes deployed in food industry applications: chemical sensors, biological sensors (biosensors), optical sensors, physical sensors, and nanosensors[13]. Each class occupies a specific niche within the quality monitoring workflow, and their integration within a multisensor platform provides a holistic assessment capability that far exceeds any single-modality approach.

Chemical sensors – primarily electrochemical and metal-oxide-semiconductor (MOS) gas sensors – detect concentrations of volatile organic compounds (VOCs), CO2, O2, NH3, H2S, and other gaseous markers of microbial spoilage. Arrays of gas sensors with partially overlapping selectivity profiles, processed by pattern recognition algorithms, constitute "electronic noses" (e-noses) capable of discriminating between fresh, marginally acceptable, and spoiled meat, fish, and dairy products. Recent implementations incorporating machine learning classifiers detect spoilage 2–4 hours earlier than human organoleptic assessment, providing a critical intervention window[14]. Electrochemical biosensors – employing enzyme-functionalized electrodes, immunosensors, or aptasensors – enable highly selective detection of specific pathogens (Salmonella spp., E. coli O157:H7, Listeria monocytogenes) and toxins at concentrations relevant to food safety regulation.

Optical sensors are among the most rapidly advancing technologies in food quality monitoring. Near-infrared (NIR) spectroscopy enables non-destructive, real-time determination of moisture, fat, protein, and starch content in bulk grain, flour, and processed food streams, with measurement cycles of seconds compatible with high-speed production lines. Hyperspectral imaging systems combine spatial and spectral information to detect surface defects, foreign

[12] Plakantara S.P. Op. cit. *npj Science of Food*. 2026.

[13] Sensor technologies in the food industry under industry 4.0. Food Control. 2026. https://doi.org/10.1016/j.foodcont.2026.002288.

[14] Muller W. A. et al. Enhancing Food Safety in the Cold Chain Through IoT and AI. *Journal of Food Science*. 2026. PMC: https://pmc.ncbi.nlm.nih.gov/articles/PMC12910151.

body contamination, and heterogeneous composition at the individual product level. Fluorescence-based sensors exploit the intrinsic fluorescence of food chromophores (chlorophylls, myoglobin, riboflavin) as indicators of food quality. Laser-induced breakdown spectroscopy (LIBS) is emerging as a tool for rapid elemental analysis and origin authentication.[15]

Physical sensors provide the foundational monitoring layer for cold chain management. Temperature loggers based on NTC thermistors or platinum RTDs offer measurement accuracies of +/–0.1–0.5 degrees Celsius across the range from –40 to +85 degrees Celsius, relevant to frozen, chilled, and ambient food storage. Capacitive humidity sensors monitor relative humidity with resolutions of 0.1% RH, critical for preventing moisture-driven spoilage in dry goods and condensation-induced quality loss in chilled products. Time-Temperature Indicators (TTIs) – colorimetric or electrochemical devices integrated into packaging – provide a cumulative record of thermal exposure history, enabling the inference of remaining shelf life without electronic infrastructure[16]. The combination of TTI data with IoT connectivity (NFC or QR code scanning) allows consumers and logistics operators to access real-time product status via smartphone, creating a closed-loop freshness communication channel.

The transformation of raw multi-channel sensor data into reliable quality judgments is accomplished through a hierarchy of data fusion algorithms operating at three levels. At the signal level, raw sensor outputs are filtered for noise (Butterworth, Kalman), baseline-drift compensated, and cross-sensitivity corrected to produce calibrated physical measurements. At the feature level, statistical and spectral descriptors – mean, variance, rate of change, fast Fourier transform coefficients – are extracted from time-windowed sensor streams to characterize the dynamic evolution of product quality. At the decision level, classifier ensembles – random forests, support vector machines, convolutional neural networks (CNNs), and long short-term memory (LSTMs) – integrate features from multiple sensing modalities to produce categorical quality grades or continuous shelf-life estimates[17].

The deployment of inference models on edge microcontrollers under the TinyML paradigm – using frameworks such as TensorFlow Lite for Microcontrollers, Edge Impulse, or STM32Cube.AI – enables latency-free, privacy-preserving quality assessment at the sensor node itself, without data

[15] Plakantara S.P. Op. cit.

[16] IoT-Enabled Biosensors in Food Packaging. SmartFoodSafe White Paper. 2025. URL: https://smartfoodsafe.com/wp-content/uploads/2025/11/IoT-Enabled-Biosensors-in-Food-Packaging-A-Breakthrough-in.pdf (accessed: 14.05.2026).

[17] Multimodal AI for Real-Time Food Safety and Quality. *Food Science & Nutrition.* 2025. https://doi.org/10.1002/fsn3.71534.

transmission to external servers. Model quantization techniques (INT8, INT4) reduce model footprints to tens of kilobytes while retaining classification accuracy within 2–5% of full-precision equivalents, making TinyML deployments feasible on microcontrollers with as little as 256 KB of flash memory[18]. This architectural choice has profound implications for food safety in bandwidth-constrained environments such as refrigerated shipping containers, cold stores, and rural processing facilities, where reliable cloud connectivity cannot be assumed.

3. IoT monitoring systems as an enabler of ESG strategy in the food industry

The operationalization of ESG commitments in the food industry requires a robust data infrastructure capable of generating, storing, and communicating verifiable evidence of environmental and social performance across complex, multinational supply chains. IoT-based multisensor systems are uniquely positioned to fulfil this infrastructure role, providing the continuous, machine-readable data streams that ESG reporting frameworks – GRI Standards, SASB Food & Beverage Standards, TCFD, and the forthcoming IFRS Sustainability Disclosure Standards – increasingly require[19]. The OECD Global Corporate Sustainability Report 2025 underscores that credible ESG performance measurement is conditional on digital data infrastructure that eliminates reliance on self-reported, manually compiled metrics.

From the perspective of the Environmental dimension, IoT monitoring systems contribute to ESG goals through three primary pathways. First, real-time temperature and humidity monitoring in cold chain environments enables early detection of thermal excursions that would otherwise result in product spoilage and disposal, directly reducing food waste and its associated greenhouse gas emissions (methane from organic waste decomposition contributes approximately 8–10% of global anthropogenic emissions)[20]. Second, energy consumption monitoring of refrigeration equipment, combined with predictive maintenance algorithms driven by vibration and thermal sensor data, reduces both energy use and the frequency of equipment failures that cause product loss. Third, the digitization of material flow data enables precise measurement of waste generation rates and water consumption at each production stage,

[18] IONI AI. Food Industry 4.0 vs. Food Industry 5.0. 2025. URL: https://ioni.ai/post/food-industry-4-0-vs-food-industry-5-0-whats-changing-in-the-future-of-food-manufacturing (accessed: 14.05.2026).

[19] OECD. Global Corporate Sustainability Report 2025. https://doi.org/10.1787/bc25ce1e-en.

[20] Digital Transformation as the driving force for green production. Tridge Analytics. 2025. URL: https://www.tridge.com/news/digital-transformation-the-driving-force-hel-soofnd (accessed: 14.05.2026).

providing the granular data required for carbon footprint calculation and Scope 3 emissions disclosure under TCFD and CSRD frameworks[21].

The Social dimension of ESG is advanced through IoT systems in several interconnected ways. Consumer-facing transparency – enabled by scanning QR codes or NFC tags on IoT-connected smart packaging – provides immediate access to complete product provenance, processing conditions, and shelf-life status, empowering informed consumer choice and reducing unnecessary waste driven by misinterpretation of date labels. In production environments, wearable IoT sensors monitoring workers' physiological status and ambient conditions (temperature, noise levels, chemical exposure concentrations) support occupational health and safety management, a key social indicator assessed by SASB and GRI standards[22]. Furthermore, the deployment of automated monitoring systems at critical control points reduces the physical burden on quality assurance personnel, replacing repetitive manual inspection tasks with exception-based workflows that allow human judgment to focus on complex, high-value activities.

The governance implications of IoT-enabled food monitoring are particularly significant for regulatory compliance and supply chain accountability. Automated, tamper-evident digital records generated by IoT sensor networks provide regulators, auditors, and certification bodies with objective evidence of HACCP compliance, cold chain integrity, and traceability down to batch or individual unit level. The integration of blockchain-based immutable ledgers with IoT data streams further strengthens audit trails: sensor readings timestamped and anchored to a distributed ledger cannot be retroactively altered, providing a cryptographically verifiable compliance record[23]. This capability is directly responsive to the provisions of the EU General Food Law Regulation (EC 178/2002) and the requirements of the EU Farm-to-Fork Strategy regarding end-to-end traceability.

Recent empirical research on European food sector enterprises confirms the strategic value of this integration: companies that combine digital transformation investments with structured ESG reporting demonstrate measurably better financial performance than digital-only or ESG-only adopters[24]. The mechanism appears to operate through multiple channels: IoT-driven efficiency gains lower

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21 Meemken E.-M. et al. Digital innovations for monitoring sustainability in food systems. Nature Food. 2024. Vol. 5. P. 656–660. https://doi.org/10.1038/s43016-024-01018-6.

22 BDO Ukraine. Smart systems and occupational safety: innovations shaping the future. 2025. URL: https://www.bdo.ua/uk-ua/insights-2/information-materials/2025/smart-systems-and-occupational-safety (accessed: 14.05.2026).

23 A review of IoT, AI, and blockchain integration for bacterial contamination detection in food. Food Control. 2026. https://doi.org/10.1016/j.foodcont.2026.011312.

24 Marczewska M. et al. Op. cit.

operational costs; ESG compliance reduces regulatory risk; and transparent sustainability disclosure enhances brand equity and customer loyalty. In the Ukrainian agri-food context, an empirical analysis covering the period 2020–2024 has similarly identified a positive correlation between resource efficiency – as measured by digitally monitored process indicators – and composite ESG scores, suggesting that the business case for IoT investment in food safety monitoring is robust across diverse institutional environments.

A comprehensive ESG monitoring architecture for a food enterprise would encompass five functional tiers: (I) primary data acquisition via multisensor IoT nodes; (II) edge analytics for real-time HACCP compliance verification; (III) cloud aggregation and longitudinal trend analysis; (IV) ESG performance dashboard integrating IoT-derived environmental KPIs with social and governance metrics; and (V) automated regulatory and stakeholder reporting compliant with GRI, SASB, and TCFD disclosure requirements. This architecture transforms IoT infrastructure from a purely operational tool into an integrated corporate governance asset, embedding environmental accountability into the enterprise's real-time operational fabric[25].

CONCLUSIONS

The analysis presented in this chapter demonstrates that multisensor IoT systems represent a mature and strategically significant technology for the food industry, capable of simultaneously addressing operational efficiency imperatives, food safety regulatory requirements, and ESG accountability obligations. The multilayer architecture, combining sensor nodes, edge computing, LPWAN connectivity, and cloud analytics, provides a scalable, modular foundation adaptable to diverse production and logistics contexts – from single-site manufacturing facilities to geographically distributed cold chain networks.

The integration of heterogeneous sensor modalities – chemical, optical, biological, and physical – within a single multisensor platform, processed through hierarchical data fusion algorithms, achieves quality assessment accuracy that fundamentally exceeds the capabilities of any individual sensing technology. The operationalization of TinyML inference on embedded microcontrollers extends intelligent quality assessment to the network edge, enabling autonomous, latency-free decision-making in bandwidth-constrained environments. These capabilities translate directly into measurable reductions in food waste, spoilage, and product recalls.

[25] Food wastage analysis framework using comprehensive IoT solutions. *Global NEST Journal*. 2025. https://doi.org/10.30955/gnj.007826.

From the ESG perspective, IoT monitoring infrastructure generates the continuous, machine-readable, auditable data streams that underpin credible environmental disclosure, occupational safety management, and supply chain governance. Empirical research confirms that food enterprises combining digital transformation with structured ESG reporting achieve superior financial performance, establishing a compelling business case for investment in multisensor IoT systems beyond their immediate operational benefits. The integration of blockchain-based immutable audit trails with IoT data further elevates governance standards to meet the expectations of regulators, investors, and consumers alike.

Promising directions for future research include: the development of standardized interoperability protocols for heterogeneous food IoT ecosystems within the Industry 5.0 framework; the systematic assessment of cybersecurity vulnerabilities in food IoT infrastructure and the design of sector-specific threat mitigation frameworks; and the quantification of the lifecycle carbon footprint of IoT sensor deployment and operation, enabling accurate net environmental benefit calculation for inclusion in Scope 3 ESG disclosures.

SUMMARY

This chapter provides a comprehensive analysis of multisensor IoT systems for food quality and safety monitoring in the context of Industry 4.0 and ESG frameworks. The multilayer system architecture – spanning sensor nodes, edge computing, LPWAN communication, and cloud analytics – is examined in detail, with emphasis on hardware platforms for specialized embedded systems. Five principal sensor modalities (chemical, biosensors, optical, physical, nanosensors) are reviewed alongside hierarchical data fusion methodologies, including TinyML deployment on microcontroller platforms. The chapter establishes the role of IoT monitoring infrastructure as a strategic enabler of ESG performance across environmental (waste reduction, energy efficiency, carbon footprint), social (consumer transparency, occupational safety), and governance (traceability, regulatory compliance, blockchain audit trails) dimensions. Empirical evidence from European food sector companies confirms a positive relationship between digital transformation, ESG compliance, and firm performance. Future research directions are identified in the areas of Industry 5.0 interoperability, IoT cybersecurity, and lifecycle ESG impact assessment.

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