# WP T3 - Deliverable 1.1

## Assessment report of REAMIT Technologies

Improving Resources Efficiency of Agribusiness supply chains by Minimizing waste using Internet of Things sensors (REAMIT)

# Assessment report of REAMIT technologies: a comprehensive systematic review of the technical and business landscape in the fresh produce food chain

## REAMIT: Improving Resource Efficiency of Agribusiness supply chains by Minimising waste using Big Data and Internet of Things sensors

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# Executive Summary

Continuous monitoring of food loss and waste (FLW) is crucial for improving food security and mitigating climate change. By measuring quality parameters such as temperature and humidity, real-time sensors are technologies that can continuously monitor the quality of food and thereby help reduce FLW. While there is enough literature on sensors, there is still a lack of understanding on how, where and to what extent these sensors have been applied to monitor FLW. In this paper, a systematic review of 59 published studies focused on the sensor technologies to reduce food waste in food supply chains was performed with a view to synthesising the experience and lessons learnt. This review examines two aspects of the field, namely, the type of IoT technologies applied and the characteristics of the supply chains in which it has been deployed. Supply chain characteristics according to the type of product, supply chain stage, and region was examined, while sensor technology explores the monitored parameters, communication protocols, data storage, and application layers. This article shows that, while due to their high perishability and short shelf lives, monitoring fruit and vegetables using a combination of temperature and humidity sensors is the most recurring goal of the research, there are many other applications and technologies being explored in the research space for the reduction of food waste. In addition, it was demonstrated that there is huge potential in the field, and that IoT technologies should be continually explored and applied to improve food production, management, transportation, and storage to support the cause of reducing FLW.

## Contents

# 1. Introduction

Reducing food loss and waste (FLW) is a significant concern to many fresh food producers due to its high socio-economic costs and its relationship to waste management and climate change challenges [1]. First, wasting food when other parts of the world are starving is a moral/social issue [2]. Another problem is that the earth's resources are finite and must be handled cautiously [3]. To provide a reference as to the maginutude of FLW’s cost to Earth’s resources, food waste carbon footprint has been estimated at 3.3 Gt of $CO_2$-eq each year, which represents a 6% of global greenhouse gases (GHG) emissions, and also considering that this figure excludes GHG emissions related to land use change, deforestation and organic soils management [4]. Furthermore, financial resources are squandered when food is produced but not consumed [5]. In fact, the economical costs associated with food waste have been estimated at nearly USD 1 trillion per year, of which USD 680 billion correspond to economical loses in developed countries and 310 billion in developing ones [4]. The 2030 Agenda for Sustainable Development reflects the increased global awareness of the problem, mainly Target 12.3 calls for reducing food waste along the production and supply chains [6].

The FLW can occur throughout the whole supply chain, from the agricultural stage, through producers, distributors, and retailers to the consumer level. The percentage of loss varies depending on the food product, being exceptionally high for fresh produce, e.g. around 50% of all fruits and vegetables are disposed of in the EU each year [7]. About one-third of fruit and vegetable wastes are caused by produce perishing between being harvested and reaching the consumer, mainly due to long distribution routes and inadequate technologies used in transport and storage [5].

The growing food industry and increased demand for long-term food preservation have necessitated the development of systems for readily tracking and preserving food freshness and safety [8]. Recently, digital tools have become a viable solution for FLW prevention [9,10]. Intelligent identification, tracking, monitoring, and management can be achieved with the help of digital tools, such as sensors, barcode identification equipment, laser scanners, wireless, mobile, blockchain technologies, global positioning systems, and other information sensing equipment [11–13]. These technologies can influence the FLW within the broader food security landscape [14] and continuously monitor different product types, such as meat, milk, and other food products [8]. These technologies can also facilitate the development of alternative food networks that can modify the traditional linear food chain [15]. The application of the Internet of Things (IoT), for example, can support the actors to control FLW by monitoring food quality, managing food close to its shelf life, and improving the management of inventory and store layout. At the same time, sensor technologies can help reduce FLW by administering the right physical environment, especially concerning temperature and humidity [16].

Different types of technologies are used to collect information on food products, e.g., external and internal devices. External devices are attached outside the package; examples of these devices are temperature and physical shock sensors [17]. The second type is placed inside the package, in the headspace of the package, or attached to the lid, for example, biosensors and biological growth indicators [17]. The internal sensors need a communication tool to communicate their information to the users. It is also possible to combine technologies to display food's features such as time, location, and environmental information [18,19].

The sensor can be used throughout the whole product's shelf life and supply chain (production, storage, distribution, and consumption). In the production stage, the consumption data of water, electricity, and other raw materials could be collected by sensing devices installed on manufacturing equipment [20]. During the storage stage, food temperature and air humidity can also be collected from sensors in warehouses [21]. In the transportation stage, the fuel consumption, weight of product transported, and transportation distance can be collected by sensors on vehicles [21]. Environmental emission data could be obtained from intelligent sensors and environmental monitoring systems at any stage of the supply chain [20].

As shown above, the use of new real-time monitoring technologies that are based on IoT is a promising new area in food supply chains, with applications in precision, traceability, visibility, and controllability. IoT is growing exponentially and can become an enormous source of information. However, although it is expected that these new technologies will bring more efficient, and sustainable food chains in the near future, little attention has been paid to its potential use in the food sector. Thus, this study contributes to the research gap on the lack of understanding of the applications of real-time monitoring technologies based on IoT devices in the food sector and the common practices associated with these technologies.

In this sense, it is necessary to study systematically and thoroughly the potential applications of intelligent monitoring equipment to reduce food waste issues. To achieve this goal, the study discussed in this paper encompasses a systematic literature review to address the following research

questions: (1) what are the main characteristics of the food supply chain that have used food monitoring technologies to date? and (2) what real-time monitoring technologies have been deployed for these food supply chain applications?

The review was conducted by searching for studies published in peer-reviewed indexed journals in an electronic database in the last 20 years.
Scientific articles were first systematically screened via the Web of Science search engine (https://www.webofscience.com/). The combined search terms "food waste" or "food loss" and "dynamic" or "real-time" or "IoT" and "sensor" on titles, abstracts, and keywords, were considered. Only literature reported in English was included in the review scope. Several definitions of food loss and waste exist. For this report, food loss and waste are defined as the decrease in quantity or quality of food along the food supply chain [22]. Therefore, studies investigating the post-treatment of food

waste were integrated into the review scope. Food waste prevention was considered a management option; hence life cycle assessment (LCA) studies on this topic were kept in the review.

The literature search resulted in a total of 313 potentially relevant articles. In a second step, all proceeding abstracts, review articles, book chapters and grey literature were excluded, and only full-length articles were selected, totalling 199 articles. In a third step, an additional screening was made to check the relevance of the articles. The relevance of each study was assessed based on the abstract of the articles; in case of doubt, the entire paper was read. After the additional screening, 59 articles were selected for the quantitative analysis.

Before performing the analysis on the selected articles, a brief introduction to the Internet of Things (IoT), of which many of the technological solutions are based upon, is provided to aid in conceptual understanding for the reader.

# 2. The Internet of Things

The European Union Agency for cybersecurity (ENISA) defines the Internet of Things as "a cyber-physical ecosystem of interconnected sensors and actuators, which enable intelligent decision making" [25]. Information is at the centre of IoT, feeding into a continuous cycle of sensing, decision-making, and actions, as stated in the definition. Anything from a smartwatch to a cruise control system with sensors might be considered a "thing" in the Internet of Things (e.g. temperature, humidity, light, location, etc.). The communication protocol (Wi-Fi, RFID, Bluetooth, 3G/4G, etc.) are other components of the IoT ecosystem and facilitate communication with other machines or humans and computing resources. The IoT architecture typically includes four layers, as described in Figure 1.

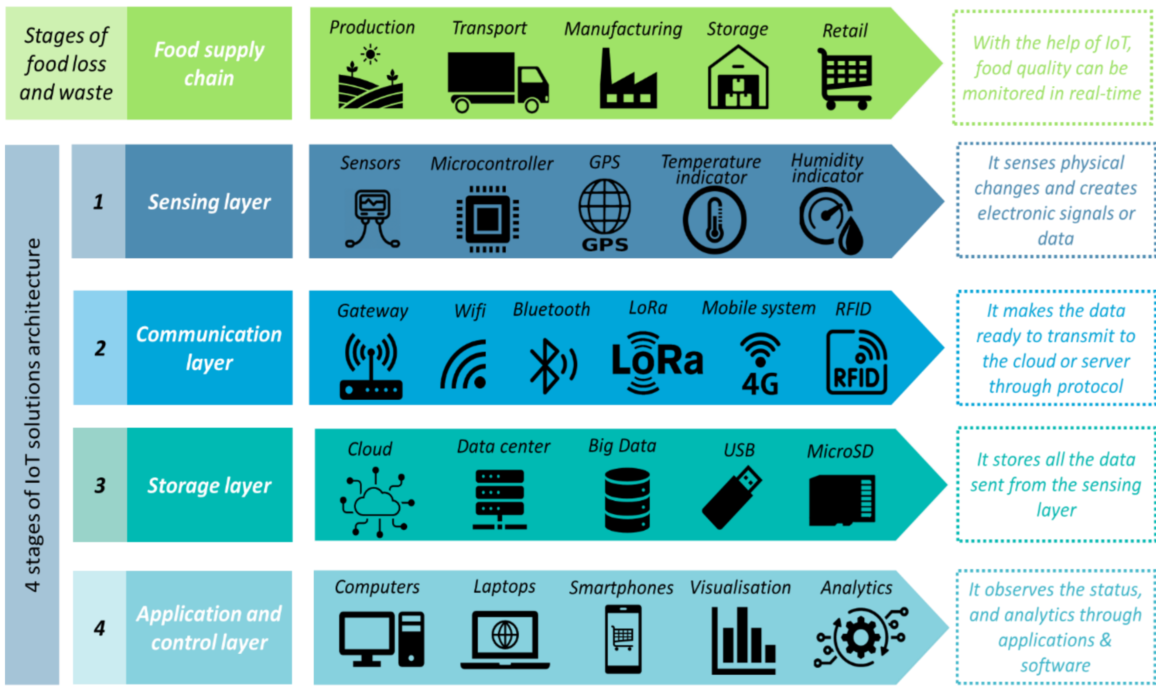


***Figure 1 IoT architecture: i) sensing layer, ii) communication layer, iii) storage layer, iv) application and control layer.***

i) Sensing layer: encompasses all devices implemented in the environment, such as sensors (e.g. temperature, light, motion and location, etc.), energy supply devices (e.g. batteries, solar panels) and other devices that can manage functionalities.

ii) Communication layer: includes devices that transmit and receive data over the communication system directly or via gateways (e.g. receptors and transmitters). It also encompasses all necessary communication technologies, wired and wireless, such as Wi-Fi, Zigbee, Bluetooth, 3G/4G, LoRaWAN, etc. It provides functionality for the network, i.e. connectivity, mobility, authentication, authorisation, and accounting.

iii) Storage layer: includes data processing and storage, as well as dedicated functionality for each application and service, since emerging services have diverse requirements.

iv) Application and control layer: this layer deals with the analysis of the data retrieved from the storage layer allowing the end user to make informed decisions based on computational intelligence methods applied to the data. Additionally, it provides applications and services that farmers, retailers, analysts, and consumers can employ. Consumers can look for product expiration dates, test reports, quality guarantee periods, product photos, and customer evaluations in this layer. It refers to the typical management and performance visualisation (i.e. software app, etc.).

# 3. Business Landscape

Food waste is recognised as a significant threat to food security, the economy, and the environment. Efforts to overcome the challenges of reducing this type of waste using IoT technologies over the years have been found throughout literature, with solutions documented as early as 2008. According to Figure 2, which presents the number of publications per year included in this review, there has been an exponential increase in research being conducted in this topic. The increase observed during the years is perhaps due to the intensified commercialisation of sensors, which is linked to the increasing awareness of the population and companies about the effects of food waste generation. The oldest publication selected is from 2008, and the most recent is from 2021 (which is the latest year of this review).

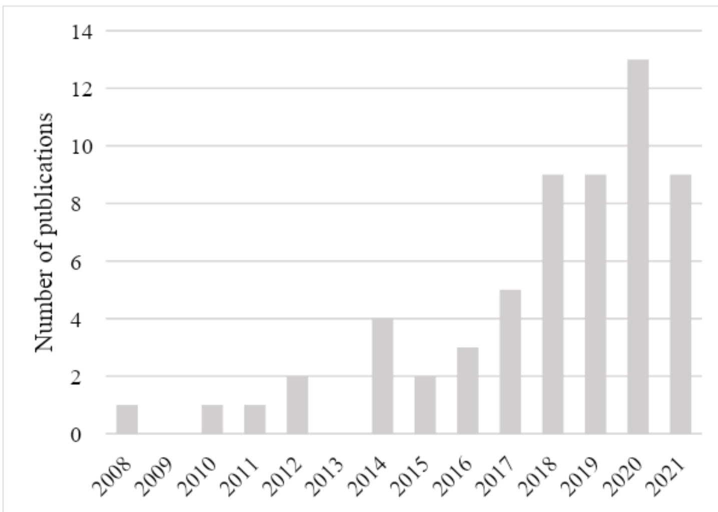


***Figure 2 Number of publications per year.***

Figure 3 shows the co-occurrence network visualisation of content for the selected publications. In this study, the keywords were grouped into three main clusters. The main terms covered in the blue cluster are related to IoT, the Internet of things and sensors. The red cluster consists mainly of management, food waste, and design terms, while the yellow cluster is more focused on temperature, traceability and cold chain.

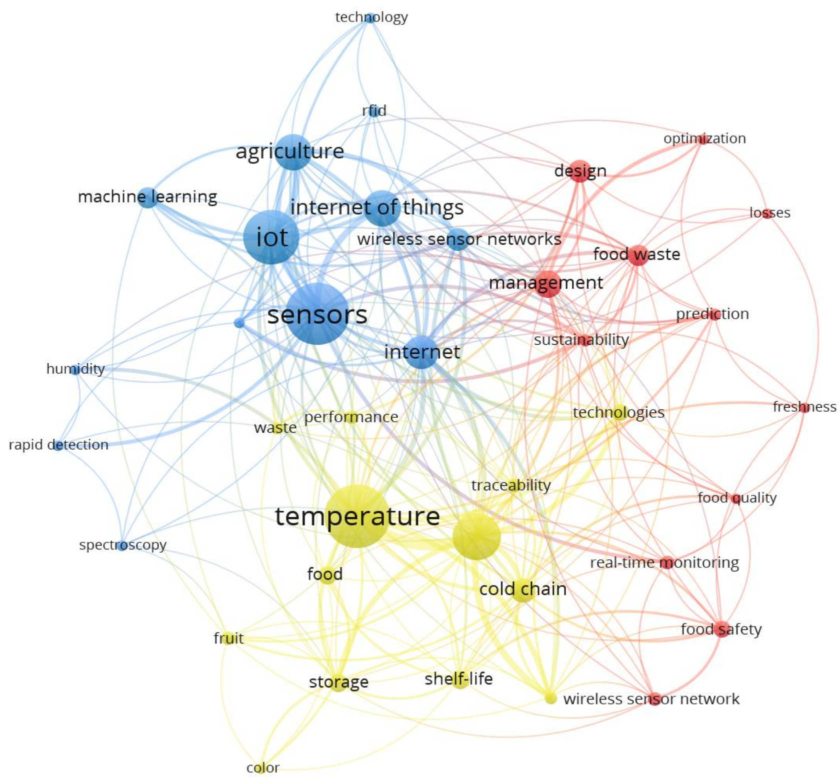


*Figure 3: Network Visualization of the content.*

To respond the first research question to understand the common characteristics of the food supply chain in which real-time monitoring technologies have been applied, relevant factors (food type, supply chain stage, and country) were extracted from each identified study and are presented in Table 1.

**Table 1. Selected papers in the chronological order of publication and main characteristics.**

| Reference | Food type | Supply chain stage | Country |
|---|---|---|---|
| Zhu et al. [26] | Garlic scape | Transportation | China |
| Afreen and Bajwa [27] | Fruit and vegetables | Storage | Pakistan |
| Torres-Sanchez et al. [28] | Lettuces | Transportation and storage | Spain |
| Siddiqui et al. [29] | Rice | Manufacturing | Bangladesh |
| Aytaç and Korçak [30] | Fast-food | Retail | Turkey |
| Zheng et al. [31] | Water | Manufacturing | China |
| Li [32] | Fruit and vegetables | Transportation | China |
| Nair et al. [33] | Banana | Storage | India |
| Sharif et al. [34] | Perishable products | Storage | UK |
| Ibba et al. [35] | Apple and bananas | Storage and transportation | Italy |
| Catania et al. [36] | Aromatic herbs | Manufacturing | Italy |
| Lu et al. [37] | Perishable products | Transportation | Taiwan |

| | | | |
|---|---|---|---|
| Wang et al. [38] | Blueberries, sweet cherries, apples | Transportation | China |
| Feng et al. [[39] | Shellfish | Storage | China |
| Zhang et al. [40] | Sweet cherry | Transportation | China |
| Torres-Sánchez et al. [41] | Lettuces | Transportation and storage | Spain |
| Urbano et al. [42] | Pumpkin and oranges | Transportation and retail | Spain and Ireland |
| Feng et al. [43] | Salmon | Storage | China |
| Markovic et al. [44] | Meat | Transportation | UK |
| Ramírez-Faz et al. [45] | Dairy products, charcuterie, meat, and frozen products | Storage and retail | Spain |
| Seman et al. [46] | Perishable products | Storage | Malaysia |
| Alfian et al. [47] | Kimchi | Storage | South Korea |
| Banga et al. [48] | Chickpea | Storage | India |
| Feng et al. [49] | Shellfish | Transportation and storage | China |
| Jara et al. [50] | Perishable products | Transportation | Ecuador |
| Baire et al. [51] | Bread | Manufacturing | Italy |
| Jilani et al. [52] | Meat | Storage | Pakistan |
| Mondal et al. [53] | Perishable products | Manufacturing, transportation, storage and retail | USA |
| Lazaro et al. [54] | Apple and banana | Retail | Spain |
| Tsang et al. [55] | Meat and fruit | Storage | China |
| Popa et al. [56] | Onion | Storage | Romania |
| Tsang et al. [57] | Meat and seafood | Storage | China |
| Tsang et al. [58] | Apple, Grapefruit, Mango, Melons, Tomatoes | Transportation | Hong Kong |
| Wen et al. [59] | Food waste | Retail | China |
| Wang et al. [60] | Holly | Transportation | China |
| Wang et al. [61] | Peach | Manufacturing, storage, transportation, retail | China |
| de Venuto and Mezzina [62] | Perishable products | Storage | Italy |
| Morillo et al. [63] | Hot and cold meals | Transportation | Spain |
| Chaudhari [64] | Perishable products | Storage | India |
| Tervonen [65] | Seed potatoes | Storage | Finland |
| Jedermann et al. [66] | Banana | Transportation | Germany |
| Xiao et al. [67] | Grapes | Transportation | China |
| Tsang et al. [68] | Meat, seafood, vegetables, fruits, wine and dairy products | Storage | China |
| Alfian et al. [69] | Kimchi | Transportation and storage | South Korea |
| Musa and Vidyasankar [70] | Blackberry | Transportation and storage | Mexico and USA |
| Seo et al. [71] | Seafood | Retail | South Korea |
| Xiao et al. [72] | Seafood (tilapia) | Transportation and storage | China |
| Shih et al. [73] | Braised pork rice | Production, storage, transportation, and retail | Taiwan |
| Thakur and Forås [74] | Chilled lamb products | Transportation | Norway |
| Badia-Melis et al. [75] | Citric fruits and different varieties of nuts | Storage | Spain |
| Chen et al. [76] | Perishable products | Transportation | Taiwan |
| Aung and Chang [77] | Banana | Transportation | South Korea |
| Eom et al. [78] | Pork meat | Transportation and storage | South Korea |
| Smiljkovikj et al. [79] | Grapes | Production | Macedonia |

| | | | |
|---|---|---|---|
| Hafliðason et al. [80] | Seafood (cod) | Transportation | Iceland |
| Bustamante et al. [81] | Poultry | Production | Spain |
| Faccio et al. [82] | Food waste | Waste collection | Italy |
| Wang et al. [83] | Perishable products | Transportation | Hong Kong |
| Ruiz-Garcia et al. [84] | Fruit | Transportation and storage | Spain |

*Perishable products include food products in general that were not specified by the authors.

## 3.1 Product type

Given that products are what defines a business, categorising the research by the food type monitored is a core analysis to perform when examining the business landscape of deployed IoT systems. To investigate trends, food type was checked for each identified research paper based on the produce being monitored during the real-world testing of the IoT system. Table 1 shows that there are 81 food types or applications monitored over the 59 studies, of which 45 are unique. These 45 unique monitoring applications can be reduced into the following 9 categories: Fruit (general fruits, banana, apple, sweet cherry, blueberry, blackberry, grapes, pumpkin, orange, peach, citric fruit, grapefruit, mango), Vegetable (general vegetables, garlic scape, lettuce, kimchi, potato, onion, aromatic herbs, tomatoes, melon), Meat (meat, pork, poultry, lamb, charcuterie), Seafood (general seafood, cod, salmon, shellfish, tilapia), Cereals & Legumes (chickpea, bread, rice, nuts), Prepared food (fast-food, hot and cold meals, braised pork rice), Food Waste, Drinks (Water, Wine) and Other (general perishables, frozen food, dairy products, holly).

Figure 4 presents the synthesis of the findings. The most commonly monitored application is Fruit, accounting for 31.71% of the total research. Further, by combining the Fruit and Vegetable categories from the analysis performed, this figure increases to almost half (47.56%) of the total screened food monitoring applications, which can be explained due to a variety of circumstances. Environmental elements, including temperature and relative humidity, influence and contribute to the deterioration of these food products. Compared to the other food categories, fruits and vegetables have the highest wastage rates, around 40–50% of the total product [85], as a result of their high perishability and short shelf lives. Therefore, maintaining the microbiological integrity of fresh fruits and vegetables throughout the production and distribution processes can be challenging.

The analysis found the second most popular application to be that of Seafood and Meat, representing 21.96% of the total products monitored. The popularity of monitoring these food types is consistent with other research which suggests that microbial spoilage is also responsible for a significant amount of food waste in the meat and seafood sector. Meat spoilage is primarily caused by three primary mechanisms: microbial growth, lipid oxidation and enzymatic reactions [86]. Since they offer a nutrient-rich environment with high water activity and a pH that is close to neutral and ideal for numerous bacterial species growth [87], these foods of animal origin are vulnerable to natural contamination.

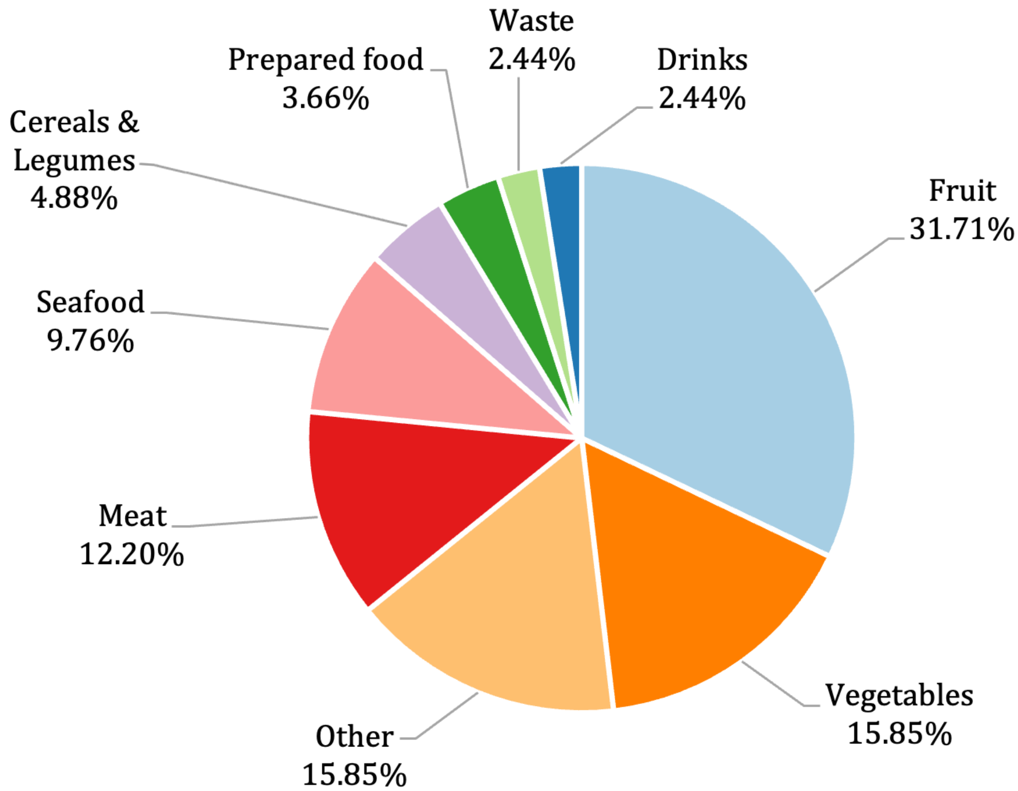


*Figure 4 Business landscape by produce.*

The Other category also accounts for a significant proportion of food types monitored (15.85%), and consists of general perishables, frozen food and dairy products. Of these categories, the majority of the research is focused on general perishables (69% of the category; 11.1% overall), which includes food products in general that were not specified by the authors. In many of these studies, the methodology proposed by the authors is a proof of concept and is not tested in the real world; thus, it could be applied to different food categories. Given that the most popular categories of monitoring are Fruit, Vegetable, Meat, and Seafood, accounting for 70.37% of all research, it is fair to assume that some of the authors of the general perishable studies intended the use of their proposed technology for one of these monitoring applications, which would increase their overall contribution.

The categories of Cereals & Legumes, Prepared food, Food waste, and Drinks, account for the remaining 13.58% of the studies. This is good evidence of the diverse nature of Food Loss and Waste Monitoring technologies and the innovative ways in which this technology can be applied.

## 3.2 Supply Chain Stage

The supply chain logistics of food products can involve many stages, such as production (crop and animal), transportation, manufacturing, storage, retail, and waste collection. The stages of the food chain most frequently examined for IoT implementation by the literature under analysis are shown in Figure 5.

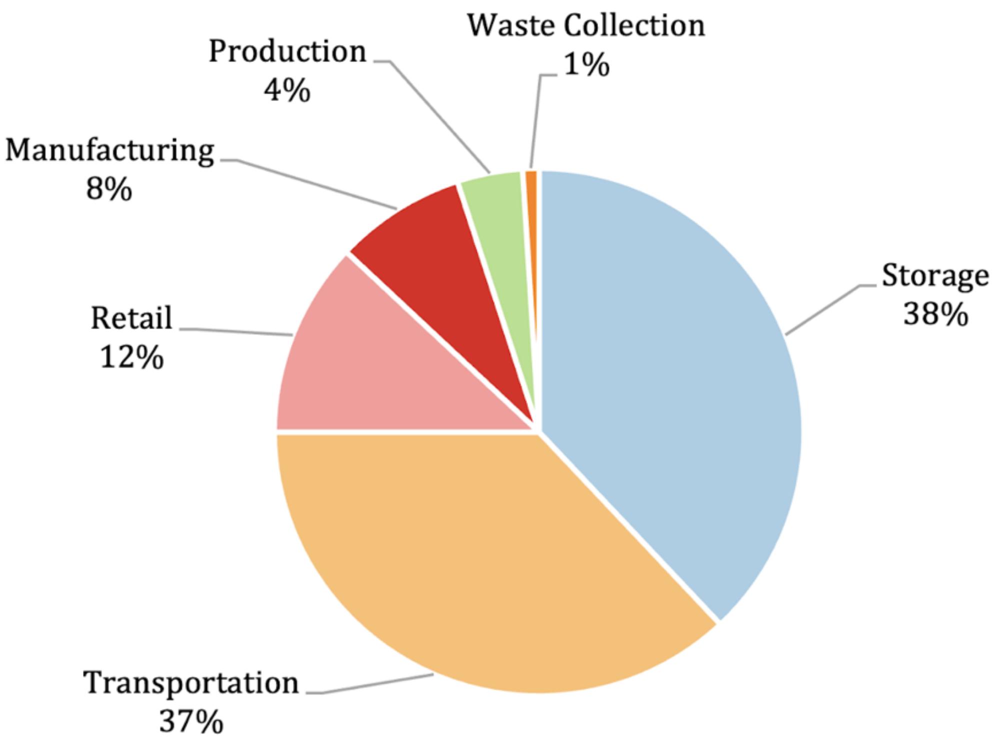


*Figure 5 Business landscape by supply chain stage*

Storage is the stage that has received more attention throughout the studies shown in Table 1 (38% of all studies), followed by transportation (37%) and retail (12%). Most food products are highly perishable and keeping them in good condition during long transportation distances and extended storage times is a sensitive problem. To reduce food loss and waste in distribution activities along the food system, it is imperative to use and monitor appropriate storage and transport conditions in real-time.

Good practices that control light, temperature, humidity, oxygen level and hygiene can significantly help to reduce losses of perishable products during storage [88]. During the transportation stage, the physical characteristics between the upper and lower levels in trucks, ships and airplanes must also be controlled and maintained, especially those moving fruits and vegetables between distant countries.

Temperature control during land transportation can be problematic, particularly at the beginning and end of the operation when loading or unloading cargo. During these activities, the temperature can temporarily rise by more than 10 °C in the refrigeration units, which can also increase the food's bacterial activity [89]. Even in developed countries, with good temperature management, the number of food products perishing during the transportation stage is high (approximately 15% of total food produced) [90]. However, as the research under investigation indicated, if alternatives to monitor and control the food quality over time were used, including the installation of IoT technology, the vast majority of food loss throughout these stages might be minimized.

## 3.3 Countries of system deployment

Another aspect to consider within the scope of the business landscape of IoT monitoring systems for FLW is exploring the regions in which these technologies have been deployed. Therefore, this section of the analysis presents the distribution of such deployed/tested systems and contains a discussion of potential reasons for their popularity within particular territories. Presented in Table 1, the papers under analysis were classed by country of origin based on the location where the IoT system was deployed for real-world testing. The 59 studies were conducted over 22 different countries in total. Figure 6 presents a visualisation of the distribution of research papers by country.

Analysing the region of studies published on real-time technology applications in the food sector, an intriguing finding is the large dominance of Chinese articles (26% of the total), followed by Spain (15%), Italy (8%), and South Korea (8%). China's high contribution to the development of technologies to monitor the condition and quality of food throughout the food chain may be due to numerous reasons, for example, China is the world's most populous country and leads the global production of various food products. China’s fruit and vegetable production accounts for 38% of global output [91]. China is also responsible for one-third of the world's reported fish production as well as two-thirds of the world's reported aquaculture production [92]. The perishable nature of these products and the high amount of waste produced may have influenced the pursuit of solutions for its mitigation.

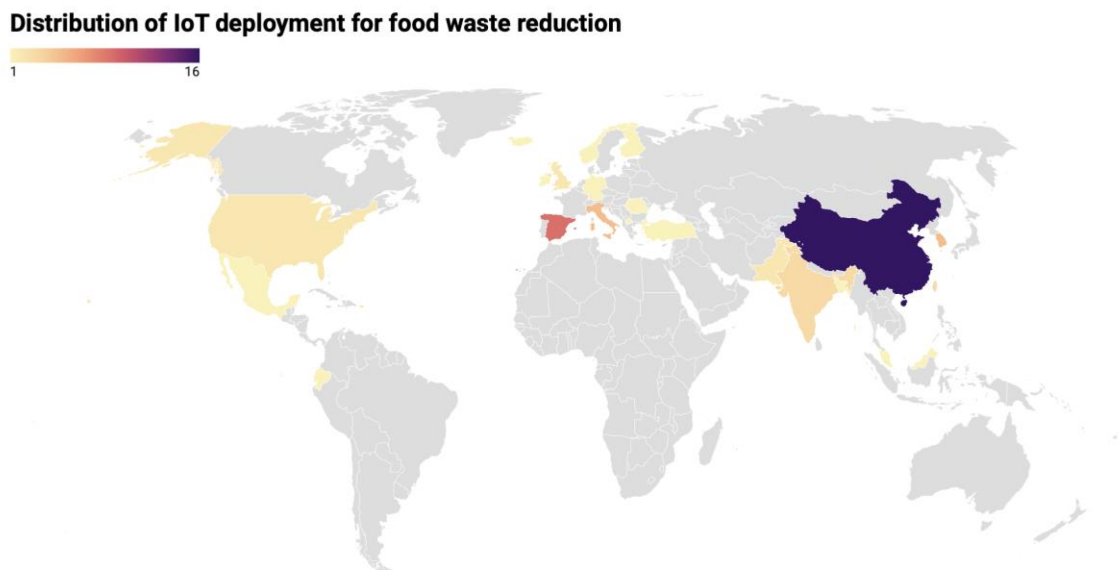


*Figure 6 World maps of the distribution of research papers by country.*

However, the scale of both the population and production is unlikely to be the sole contributor to the popularity of such IoT monitoring systems within China. For example, India is the world's second most populous country and is also the world's second largest producer of fruit and vegetable, accounting for 12% of the global output [91], yet India is only accountable for 5% of the total research articles analysed.

The disparity lies within the Gross Domestic Product (GDP) of each of the countries, which is often inextricably linked to a country's technology adoption. China has the world's second largest economy with US$17.7 trillion GDP, compared to India which has a GDP of US$2.6 trillion. It is no coincidence, therefore, that China is the world's largest IoT market with 64% of the 1.5 billion global cellular connections [93]. By 2021, the country had also installed over 1.15 million 5G base stations, which represents around 70% of the global total [94]. According to a report issued by the Internet Society of China [95], China's IoT industry exceeded 1.7 trillion yuan (€241 billion) in 2021 and is expected to reach 2 trillion yuan this year. In comparison, India's IoT market was valued at US$4.98 billion in 2020. This point can be exacerbated further by looking at the example of Brazil. Brazil is noted to feed 10% of the global population and is the 4th largest producer of fruit and vegetable [91], yet from the research papers selected in this study none originate from this country. Here, their GDP is valued at US$1.1 trillion, and the IoT revenue was valued at US$2.28 billion in 2020. As observed, China is helping shape the world's transition to the IoT, which is being driven by the incentives of private industry, and by the Chinese state's sustained policies to boost the role of Chinese actors in IoT development.

A third explanation for China's dominance in the research field is due to the introduction of the Anti-food Waste Law of the People's Republic of China in April 2021 [96]. This law has been implemented in order to guarantee grain security, conserve resources, and protect the environment. Approaching the food waste problem by creating a law with sanctions may have encouraged some businesses to take proactive measures such as deploying IoT monitoring technology to aid in the reduction of potential food waste.

Another aspect to consider in this analysis is the geoclimatic nature of the countries and if businesses located in particular regions with specific climate systems are more inclined to deploy IoT systems for the monitoring and reduction of food waste. The Köppen climate classification is one of the most widely used climate classification systems (Figure 8). The system divides climates into five main climate groups, with each group being divided based on seasonal precipitation and temperature patterns. The five main groups are A (tropical), B (dry), C (temperate), D (continental), and E (polar).

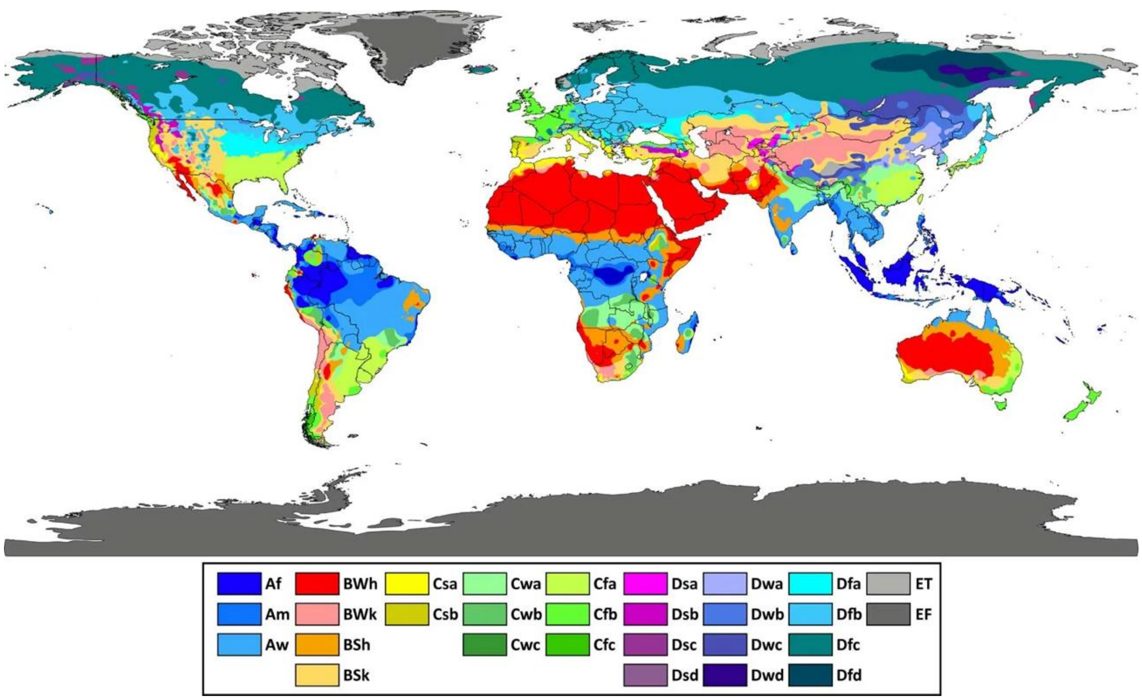


*Figure 7 Köppen climate classification map [97].*

Examining Figure 7, it was observed that the regions of East Asia and Southern Europe both fall under the temperate climate classification. Southern Europe is largely dominated by Csa classification which is "Warm summer temperate climate" and East Asia is largely dominated by Cwa which is "Warm temperate climate". 70% of the papers selected in this review were based in regions which displayed these climatic properties (China, South Korea, Taiwan, Hong Kong, Spain, Italy, Romania, North Macedonia, Turkey). One reason for this could be that agricultural production in temperate regions is highly productive due to a generally higher nutrient level in the soil [98,99]. A significant proportion of global agricultural output originates from these temperate (i.e. non-tropical) countries. Yet while these regions offer favourable conditions for agricultural production, the decomposition of foods is also accelerated by the warmer climates associated with these climate systems. For example, the Spanish agri-food industry is the country's main manufacturing activity [100], yet temperatures on the Iberian Peninsula, a region dominated by the Csa climate system, display a mean of 23 °C in summer months and are noted to exceed 45 °C on occasion. Given these warm temperatures, in an attempt to avoid the perishment of goods, researchers have been keen to deploy IoT monitoring systems in this region, observed by the 15% share of the total research articles under analysis.

# 4. Technical Landscape

This section focuses on the technologies employed throughout the literature at each of the layers that commonly conform an IoT architecture: the sensing, communication, storage and control, and application layers.

As previously discussed, FLW is a major concern for food producers not only for economic reasons but also due to increasing pressure for industries to adopt higher environmentally and socially responsible manufacturing practices. In the last decades, developments in sensor and information technology, as well as a general trend in the reduction of electronic devices' cost and size over time, are making it increasingly more accessible and affordable for industries in the food supply chain to modernise and digitalise their processes and operations [69]. In food processing, for example, the adoption of real-time sensors allows transitioning from an inferential monitoring and control approach to a continuous measurement of key quality parameters in real-time [40].

The following sections analyse and summarise the designs and technologies found throughout the literature, and provide an overview of the current state of real-time sensor applications to mitigate FLW in the different stages of the food supply chain, i.e. production, manufacturing, storage, transportation, and retail, worldwide. While doing so, the sequence shown in Figure 1 on IoT architecture will be followed.

**Table 2. Communication technologies used in food safety IoT applications.**

| Ref | Sensing technologies | Data communication | Data storage and control | Applications and softwares |
|---|---|---|---|---|
| [26] | AM2322, $CO_2$ ATI, $O_2$ ATI and ethylene ATI | WSN, 4G DTU | Database server | Keil5 and language of C |
| [27] | DHT-22, MQ-135 and LDR | ESP-WROOM-32 | Firebase database | RTIMNS android app |
| [28] | LDR NSL06S53 and DHT-22 | Wi-Fi | Database server and gateway (MicroSD) | Programmed in MicroPython based on Pycom libraries |
| [29] | ADC, RTC, LCD, temp & humidity sensors | LoRa, GPRS, 3G | Cloud server | Mobile app based on rESTful API |
| [30] | - | Zigbee, Wi-Fi | Cloud server | Naïve Bayes, ID3 algorithm, k-means |
| [31] | High-precision microbial sensor | Zigbee, Wi-Fi, Serial communication | Local HDD | NUC120 and CC2530 softwares |
| [32] | - | 5G | - | Xilinx software |
| [33] | MQ2 | Wi-Fi | Arduino Uno | Blynk application |
| [34] | RFID reader | RFID | - | XGBoost algorithm |
| [35] | EIS using AD5933 microcontroller | Serial communication | Local HDD | LabVIEW; Matlab; Matlab Zfit |

| | | | | |
|---|---|---|---|---|
| [36] | 7MH5102-1PD00 load cells, DHT-22 temp/RH | Wi-Fi | ThingSpeak (IoT cloud) | ThingSpeak online platform |
| [37] | Temp/RH sensor | MQTT | MS SQL DB | Mobile phone app, bespoke computer program (developed in VB) |
| [38] | ADC ethylene sensor; STC12C5A60S2 control chip | 4G | Cloud server | Keil UVision4 (C language); web application and android app |
| [39] | Temperature, relative humidity, O2, CO2 sensor node using Zigbee CC2530 | Zigbee, GPRS | MS SQL DB | PC and Mobile Phone user application |
| [40] | - | Serial communication | Local HDD | Keil UVision4 (C language); Matlab |
| [41] | LMT86 | Wi-Fi, GPRS | Cloud server | Multiple Linear Regression / Nonlinear Regression |
| [42] | SHT1x sensor | RFID, 3G, 4G, Wi-Fi, LoRa, NB-IoT | Cloud server | Orbis Traceability System |
| [43] | MQ136, MQ 137, MQ 138, TGS2612, TGS822, and TGS2600 | Zigbee, Serial communication | Local HDD | CNN-SVM algorithm |
| [44] | TGU-4017 and DS18B20 | Bluetooth | Ledger | PROoFD-IT app |
| [45] | DS18B20 | Wi-Fi | - | ThingSpeak / ThingChart (app) |
| [46] | DHT-11 | Wi-Fi | - | Blynk platform based on NodeMCU |
| [47] | Sense-HAT | RFID, Wi-Fi | MongoDB | Android app developed using Python |
| [48] | CZN-15E Condenser, DHT-22 | Serial communication | - | Audacity; Praat; Linear predictive coding |
| [49] | - | WSN | WSN Database | - |
| [50] | DS18B20 | WSN | Arduino Uno | - |
| [51] | DS18B20, SHT10, MQ-7 and MHZ19 | Wi-Fi | Elasticsearch | Kibana tool |
| [52] | Microwave sensor | Bluetooth, Wi-Fi | Local HDD | Application developed in LabView |
| [53] | Thermistor-based temperature sensor | RFID | Local HDD | Spyder IDE |
| [54] | TCS34725 | NFC | Cloud server | An android application was developed |
| [55] | CC2650 | Bluetooth, Wi-Fi | IBM cloud server | Food traceability system (BIFTS) |
| [56] | BME680, DHT-22 and MQ5gas | ZigBee | Excel spreadsheet | LabVIEW interface |
| [57] | CC2650 | Bluetooth, Wi-Fi, 3G, 4G | Cloud server | IoTRMS |
| [58] | SensorTag CC3200 | GPRS (3G, 4G, LTE) | My SQL | Web application, IBM IoT Watson |
| [59] | - | GPRS (4G) | - | - |
| [60] | AM2322, $CO_2$ ATI, ethylene ATI | GPRS (4G) | T-LINK database | Keil5, T-link |
| [61] | - | GPRS (4G) | Cloud server | - |
| [62] | L/H/T sensors | ZigBee | System's central control unit (Raspberry Pi 2 B+) | Python 2.7 |
| [63] | ADC 2KSPS, Carel NTC015HP0 and SensorTag CC2650 | WSN, Bluetooth, 3G, 4G | IBM cloud server | Foodmote, IBM IoT Watson |
| [64] | Simulation of sensor nodes | - | IBM cloud server | IBM IoT Watson and Apache Spark |
| [65] | - | Serial communication, Wi-Fi | Remote server located in the company | Java-based application |
| [66] | Sensor node TelosB 2.4 GHz | GSM | Cloud server | - |
| [67] | SHT11 | GPRS, WSN | | - |
| [68] | CC2650 | Bluetooth, Wi-Fi | Cloud server | Matlab |
| [69] | FTC-001 | Wi-Fi | MongoDB, NoSQL and SQL DBs | Express - Node.js based on Socket.IO |
| [70] | Intelleflex XC3 | RFID, Wi-Fi | Cloud servers | - |
| [71] | EOC biosensor | Wi-Fi | FIFO and flash EEPROM memory | Flask Station mobile app |
| [72] | DS18B20 | ZigBee | MS SQL DB | C# in Microsoft Visual Studio 2008 |
| [73] | - | ZigBee | ERP server | - |
| [74] | EPCglobal UHF Class 1 | GSM, GPRS | EPCIS based system | EPCIS system available through web interface. |
| [75] | Sensor MTS400 and MS5534B | ZigBee, IEEE | Local HDD | Matlab |
| [76] | - | RFID | Database server | Mobile app |
| [77] | MSP430 | ZigBee, IEEE | Terminal PC's API | TinyOS platform |

| | | | | |
|---|---|---|---|---|
| [78] | MSP430, MM1001, MICS-5914 | RFID | Local HDD | Smart Monitoring System |
| [79] | Waspmote sensor | XBee 868 radio | Cloud servers | SmartWine |
| [80] | iButton DS1922L and CMS sensor | WSN, RFID | WSN | - |
| [81] | Platinum resistance temperature detector (RTD) | Serial communication | Local HDD | LabVIEW 8.2 |
| [82] | Volumetric sensor | RFID, GPRS, GPS | Database server | Operations center traceability software |
| [83] | - | RFID, GPRS | Backend system | - |
| [84] | MTS420 board - Sensirion SHT | ZigBee | Local HDD | - |

*Serial communication includes USB and RS232.

**Database servers can include physical (HDD) or virtual (cloud) databases.

At its basic level, a sensor is a detection device that can measure physical or chemical information related to the sample and transform this information into an electrical signal output that can be read and interpreted by another device such as a computer [101]. Table 2 presents the different technologies employed across the various layers of IoT, from sensors to data transmission technologies to databases and software applications. From Table 2 it can be seen that a wide range of sensing technologies was investigated by the studies at different stages of the food chain. In addition, most of the sensor setups deployed are bespoke to the study, thus finding commonalities between them can be challenging.

While there is not a de-facto choice for these sensors, popular gas composition and concentration sensors include the MQ-series, for instance, MQ-2, MQ-5, MQ-7, MQ-135, MQ-136, MQ-137, and MQ-138; which were cited 7 times in the total. These sensors are suitable to detect, measure, and monitor a wide range of gases present in air like methane, ammonia, benzene, carbon dioxide, etc. Due to its high sensitivity and fast response time, it is appropriate for different applications [102]. Another gas monitoring device extensively applied in the studies under analysis was the ATI sensor. These sensors are normally applied to detect oxygen, carbon dioxide and ethylene levels and are designed to detect gases up to 20 ppm [102].

The most applied sensors in this literature review to determine the temperature along the food supply chain consisted of a range of DHT (for instance DHT-11 and DHT-22) and DS (for instance DS18B20 and DS1922L) sensors. The DHT sensors are made of two parts, a capacitive humidity sensor and a thermistor [103]. Commercially available IoT sensors commonly incorporate both parameters. A DHT sensor was employed by Catania et al. [36] to measure the surrounding air and transmit it to a microcontroller that spits out a digital signal with the temperature and humidity. These sensors are low cost, very basic and slow, but are good for users who want to do basic data logging [101]. The two versions look similar and have the same pinout, but the DHT-22 is of higher accuracy (±0.5°C, 2-5% RH) and good over a slightly larger range of temperature (-40 to 125°C) and humidity (0-100%) compared to the DHT-11 (±2°C, 5% RH; 0-50°C, 20-80% RH) [105].

The DS18B20 sensor was also widely used in the studies. It is a device that can measure temperature with a minimal amount of hardware and wiring. These sensors use a digital protocol called 1-wire to send the data readings directly to the development board without the need of an analog-to-digital converter or other extra hardware. Its accuracy ranges from -10 to 85 °C [106]. The DS1922L on the other hand, is a self-sufficient system that measures temperature and records the result in a protected memory section and the temperature range is -40 to 85°C [107]. Xiao et al. [72] used a DS18B20 to evaluate the temperature of seafood products (cod) during transportation, while Hafliðason et al. [80] applied a DS1922L to study the temperature of tilapia during transportation and storage. Both sensors were found to be efficient for the determination of temperature during the transportation of refrigerated products, but the second offers a broader range of temperatures.

As shown above, there are many different components available on the market and the sensing parameters and their corresponding ranges of detection will define what actual sensors are the most recommended for each type of application.

## 4.1 Sensing parameters

Figure 8 shows the parameters that were monitored in each selected paper for food quality preservation. The parameters presented in the column “others” include backscatter power, ripeness, sound, tissue moisture, color, acceleration and radiation. Parameters are shown left to right by order of importance in count numbers.

As can be seen from figure 8, the most frequently measured parameter in the reviewed articles was the temperature (n=48), which appeared in 81% of the selected papers. This can be explained by its crucial importance in food perishability and freshness, being paramount for microbiological growth and activity. For instance, concerning fruit and vegetables, the temperature is the most important factor to monitor and maintain within recommended ranges after harvest [28]). In fact, post-harvest losses have been estimated to account for approximately 25 % of food production worldwide [77], and hence the need to monitor temperature effectively along the fruit and vegetables’ supply chain. As known, temperature is also a very important factor for cold chain storage and transportation of meat products to prevent spoilage. Several IoT systems were deployed for meat related applications in the selected articles (n=9), and nearly all of them, with the exception of one, included temperature as a monitoring parameter. Similarly, fish and shellfish storage and transportation applications also incorporated temperature (n=7) as a sensing parameter. In general, temperature is a crucial factor for the average life of all food types as indicated by the Hazard Analysis and Critical Control Points (HACCP) guidelines [62].

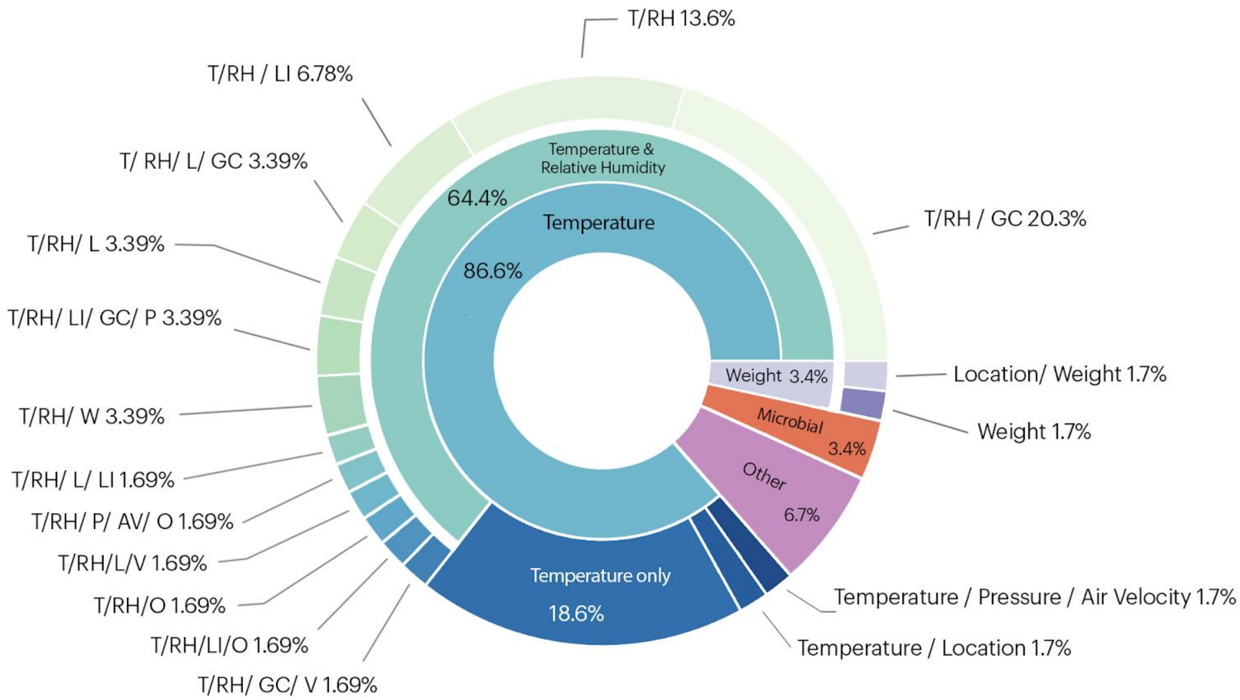


***Figure 8 Triple nested pie chart showing all the sensing parameter combinations used in the selected articles.***

With regard to the transport of refrigerated food, commonly, refrigerated trucks and facilities are set at a fixed temperature, which may not be optimal for all types of products to best preserve their safety and quality [57,74]. Tsang et al. [57] observed, however, that it can be challenging for logistic companies to remain cost-effective when shipping multiple refrigerated foods with each type kept at their recommended storage temperature, and thus often a fixed temperature is used for all. The authors proposed an intelligent model for ensuring food quality when managing multi-temperature food distribution centres. The proposed system aided in reducing food spoilage by allowing key traceability and product information, collected and processed by IoT sensors, to be accessed by staff and customers in real-time. Thakur and Forås [74] evaluated an Electronic Product Code Information Services (EPCIS) system for real-time monitoring temperature and traceability of chilled lamb products during transportation. The authors concluded that such an EPCIS system proved effective for managing temperature data in cold supply chains, yet further hardware development efforts were needed to withstand the food production environment in an industry setting.

Following temperature, relative humidity (RH), understood as the ratio of the current absolute humidity relative to the maximum humidity at a given temperature, was found to be the second most recurring parameter in the reviewed articles. Humidity also plays a huge role in microbiological growth and development, and therefore a factor of the utmost importance in food perishability, freshness and safety [108]. In the systems presented in the selected articles, RH was always measured in conjunction with temperature.

Environmental gas composition and concentration, e.g. oxygen ($O_2$), carbon dioxide ($CO_2$), ethane ($C_2H_6$) and volatile organic compounds (VOCs) constitute an important parameter to monitor and rapidly address accordingly for many foods such as fruits and vegetables. According to Afreen and Bajwa [27], however, little attention has been paid to factors other than temperature and relative humidity in monitoring the quality of fruits and vegetables in cold storage. Hence, the authors presented a real-time IoT system to help overcome the loss of perishable foods also including parameters other than temperature and RH such as concentration of $CO_2$ and light intensity. Likewise, Torres-Sanchez et al. [28] presented a wireless platform system for real-time monitoring of multiple environmental variables, including gas concentration during the movement of foods and perishable goods along the supply chain. Wang et al. [38] proposed a multi-strategy control and dynamic monitoring system for environmental ethylene quantification during fruit storage. Ethylene is a phytohormone related to quality and storage life as it induces several chemical and physical changes during the ripening of the fruit, hence the importance of monitoring and control [38]. The authors employed a microcontroller as their main control unit, connected to a transmission module communicating via the 4G wireless network.

Recording reliable location information is the basis for traceability and visibility in the supply chain. Although the location was not among the most frequent parameters in the selected articles (n=5), it must be noted that a large number of articles concerned the production or storage stages rather than transportation. Sensing of light intensity was found in 7 of the selected articles. For instance, light exposure intensity has been evaluated for agricultural product quality decay, along with temperature and RH by Venuto and Mezzina [62]. The authors developed a Wireless Sensor Networks (WSN) based system and reported an increment of about 1.2 days or 15% of the maximum product useful life of the expected expiration date with their automated, real-time system. Other, less frequently measured parameters, included pressure and weight, with four occurrences each (n=4); and microbiological concentration, vibration, and air velocity, being reported two times each (n=2). As previously mentioned, the column others referred to backscatter power, ripeness, sound, tissue moisture, color, acceleration and radiation. These sensing parameters were assessed only once and not repeated across the selected articles.

Future work could encompass other parameters not widely exploited to date to cover broader classes of sensors and additional forms of food quality assessment.

## Data communication – the communication layer

In the context of IoT, sensor devices are connected in real-time to other electronic devices, forming an interconnected network to facilitate fast decision-making. Thus, sensors in IoT need to integrate communication technologies that allow continuous, rapid data transfer, as opposed to "non-IoT" enabled systems relying on data logging for later retrieval. Figure 9 presents the communication options most frequently investigated for sensor implementation by the literature under analysis.

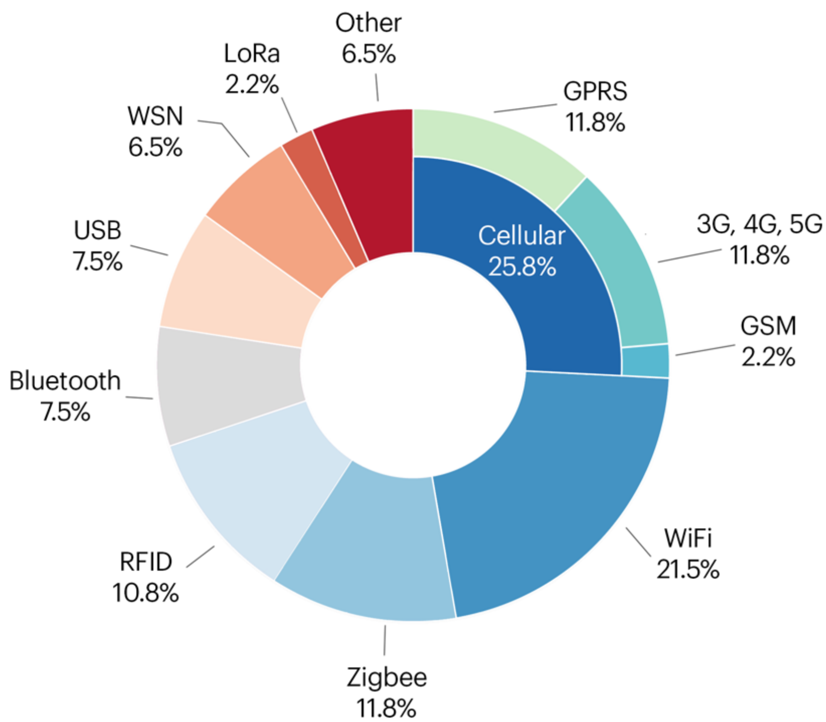


*Figure 9 Communication options for IoT applications.*

Real-time data transfer is commonly achieved through the use of different wireless communication technologies such as Wi-Fi, Radio Frequency Identification (RFID), among others [109]. In general, wireless communication has been the preferred option opposed to wired transmission in recent times since it provides a higher degree of flexibility and not necessarily at a higher cost [45].

Among the wireless communication technologies found throughout the literature specific to IoT applications in the food supply chain, as seen in Figure 9, the most frequently used systems were those based on cellular communication technologies. By combining GPRS, 3G/4G/5G and GSM into a single category, it was observed that 25.8% of the studies used these technologies. The Global System for Mobile (GSM) describes the protocols for second-generation (2G) digital cellular networks. It was used by Jedermann et al. [66] to determine the quality of bananas during transportation. The General Packet Radio Services (GPRS) is a packet-switching protocol still commonly used for wireless and cellular communication services on the 2G and 3G network's global systems. However, over the last years, GSM and GPRS have mainly been superseded by 4G and 5G mobile data technologies [110]. Tsang et al. [58] used GPRS to evaluate fruits during the transportation stage, while Wang et al. [61] used it to evaluate the quality of peaches during all stages of the supply chain. The mobile networks (3G, 4G and 5G) comprise mobile data connections that use a network of phone towers to pass signals, ensuring a stable and relatively fast connection over long distances [110]. Each generation differs from the others based on its capacities, e.g. speed (lower latency), network volume (higher bandwidth) and accessibility (longer range of service).

Wi-Fi communication was also popular amongst researchers, noted by the 21.5% share of the screened studies. As stated by Torres-Sanchez et al. [28], the main advantage of using Wi-Fi networks is the widespread and easy to install infrastructure. In fact, the authors developed a flexible multi-parameter system able to exploit this extensive availability of Wi-Fi networks along the postharvest chain; that is, a system capable of communicating and sending data via Wi-Fi at multiple locations. However, the authors also indicated its disadvantages in terms of energy consumption compared to other wireless technologies, e.g. SigFox, LoRa or ZigBee. To overcome this challenge, the authors introduced a system that incorporated synchronization algorithms to reduce the total amount of time Wi-Fi transceivers were online, receiving and sending information [28].

ZigBee was also found in 11.8% of the studies under analysis. This communication technology is a wireless IoT network-based system that was designed as an open worldwide standard based on IEEE 802.15.4 protocol. Its current use is widely spread in smart home, agriculture and medicine, among other industries. While other wireless communication technologies were designed for achieving higher distances or speed, ZigBee is committed to achieving low-speed, short-distance wireless network transmission, but offering low-power and low-cost applications in battery-powered devices.

Another of the most frequent systems was those based on RFID (10.8% of the total studies). RFID technology is a flow control technology widely used in food logistics as it enables traceability throughout the production chain from source to consumer [111]. Oftentimes, installing appropriate IoT systems is off-limits to small agribusiness given their high initial investment costs [42]. For this reason, Urbano et al. [42] presented the design and implementation of a cost-effective traceability system based on RFID for cold chain monitoring applications. As the authors mentioned, they chose RFID because of its affordability, maturity and wide adoption in the industry, and their efforts revolved around presenting an economical system. However, a drawback that the authors reported was low memory associated with the RFID chips.

Bluetooth is a short-range wireless technology standard used for transmitting data over small distances between stationary and mobile devices [112] and was cited in 7% of studies. It was used by Markovic et al. [44] to monitor the quality of meat during transportation. Additionally, it was combined with Wi-Fi in three other studies [52,55,68]. Wireless Sensor Networks (WSN) was also found in a number of studies (6.5%). It is formed by arrays of sensors interconnected by a wireless communication network.

More specifically, WSNs are made up of sensor "nodes" where each of them shares sensor data and consists of one or more sensing units, an embedded processor, and low-power radios. The nodes can act as information sources but also as "information sinks", receiving dynamic configuration information from other nodes or external entities [113]. Advantages include ease of deployment, low device complication and low consumption of energy [114]. Table 3 presents the characteristics of the main communication technologies available on the market in terms of frequency, data rate, range, energy consumption, etc.

**Table 3. Communication technologies' main characteristics. Adapted from Kazeem et al. [115] and Singh et al. [115,116].**

| Technical features | Wi-Fi | RFID | Zigbee | GPRS/GSM | Bluetooth |
|---|---|---|---|---|---|
| Standard | IEEE 802.11 | Several | IEEE 802.15.4 | - | IEEE 802.15.1 |
| Frequency | 2.4 GHz | 13.56 MHz | 868/915 MHz, 2.4 GHz | 850-1900 MHz | 2.4 GHz |
| Data rate | 2-54 Mbps | 423 kbps | 20-250 kbps | 20-85 kbps | 1-24 Mbps |
| Transmission range | 20-100 m | 1 m | 10-20 m | 10 m | 8-10 m |
| Energy consumption | High | Low | Low | Low | Medium |

Bluetooth, ZigBee and Wi-Fi protocols have spread spectrum techniques in the 2.4 GHz band, which is unlicensed in most countries and known as the industrial, scientific, and medical (ISM) band. Bluetooth uses frequency hopping (FHSS) with 79 channels, while ZigBee and Wi-Fi use a direct sequence spread spectrum (DSSS) with 16 and 14 channels, respectively [117]. Based on the bit rate, GPRS and ZigBee are suitable for low data rate applications (such as mobile devices and battery-operated sensor networks). On the other hand, for high data rate implementations (such as audio/video surveillance systems), Wi-Fi and Bluetooth would be better solutions.

As for range, it can be distinguished between short-range networks such as Bluetooth, ZigBee, RFID, or long-range such as Wi-Fi. In general, Bluetooth and ZigBee are intended for WPAN communication (about 10m), while Wi-Fi is oriented to WLAN (about 100m). However, ZigBee can also reach 100m in some applications [118]. ZigBee and RFID are designed for portable devices with short ranges and low battery power. It therefore has a very low power consumption and, in some situations, has no measurable impact on battery life. Wi-Fi and Bluetooth, on the other hand, are made to support devices with a strong power supply and longer connections.

Therefore, it is not possible to determine which communication technology is superior because the suitability of network protocols is greatly influenced by real-world applications and many other factors need to be taken into account, such as, network re-liability, roaming capability, price and installation costs.

## 4.3 Data storage – the storage layer

As previously mentioned, sensors in an IoT network are continuously collecting and sending information to be processed and modelled through appropriate algorithms, which results in massive amounts of data over time; hence, in the context of IoT, the term "big data" is often employed [119]. To allow for storage and subsequent analysis of big data, IoT architectures contain a dedicated storage layer which often employs database management tools with data being stored either locally or remotely.

In general, it can be seen in Table 2 that authors chose to store data either locally, using physical servers such as hard disk drives, single-board computers, and databases residing on local drives or local area networks; or remotely, using cloud-based platforms or remote database servers. The use of PC-based or local hard disk drives (HDD) options was seen across 10 (17%) of the selected papers. An example of single-board computers was found in the warehouse management system proposed by De Venuto and Mezzina [62]. The authors employed a Raspberry Pi 2 B+ as the central control unit where a set of Python 2.7 scripts were implemented for the computing of product shelf-life modelling, first-to-expire first-out management and automatisation of pallet transporters for displacement of perishable products.

Although a wide diversity of data management solutions was found, among the range of possibilities reported in Table 2, one of the preferred options was relational database systems (n=5) such as Microsoft Structured Query Language database (MS SQL DB) and MySQL server. Relational databases, often referred simply as SQL databases after the query language they are based on, are regarded as highly efficient for storage and management of structured data, i.e. predefined and formatted into precise table fields, delivering data consistency and complex query execution while facilitating the subsequent application of algorithms or Machine Learning (ML) techniques at the same time [120]. SQL database softwares retrieve and store data from other software applications, which may run either on the same computer or on another computer across a network. As an example of a SQL database implementation, Lu et al. [37] used Microsoft SQL server management studio for storing and querying data in their proposed real-time temperature and humidity monitoring system of a smart refrigerator.

In contrast, a larger number of publications employed cloud server platforms (n=27) such as IBM cloud, Firebase, ThingSpeak, etc. In this regard, a higher degree of flexibility may be required when working with large sensor generated datasets consisting of not necessarily structured data. NoSQL databases, which were used in several of the selected research articles in Table 2, allow management of unstructured data, or data of low structuredness level. To do so, it prioritises data availability at the expense of consistency, yet achieving stable, fast read and write operations when dealing with copious amounts of data data [69,120]. Specifically, Alfian et al. [69] employed MongoDB which is a flexible open-source NoSQL database that stores data based on collections and documents rather than the two-dimensional row and column approach of relational databases [121]. This way, allowing storage of the large volumes of unstructured sensor data continuously collected from multiple sensors in their proposed real-time monitoring system of perishable products [69]. Likewise, the Firebase Database, which is a NoSQL cloud database, was implemented by Afreen and Bajwa [27]. Elasticsearch was also used once in the literature, in the study by Baire et al. [51]. Although more commonly regarded as a search and analytics engine, Elasticsearch constitutes an open-source tool, built using Java, that supports storage of data in an unstructured NoSQL format [122].

As it was observed, the large majority of the studies under analysis have selected cloud databases instead of traditional databases to store and manage their information. The first observed pro of using a cloud is that the data stored in the cloud can be accessed from wherever there is an internet connection [123]. It is also extremely scalable and elastic, giving the opportunity to start small and expand the database if more space is required, mitigating the risk and uncertainties of investing in IT equipment [124]. A final pro is that data is also stored remotely and never stored on the computer, meaning that it will be safe in the cloud if there are technical issues [124]. On the other hand, one disadvantage of using cloud databases is the reliance on an internet connection. If the connection is not strong, some difficulties in accessing the data can be observed. However, some software already allows offline access and synchronises the edits later.

On the other hand, the first advantage of using a traditional database is the speed you can up/download data to the server [125]. Having a local server on-site can also increase security because only the organisation can access it physically and digitally [125]. In addition, the companies have total control over the system setup, to make sure it fits their exact needs. The main con of having a local database is needing to install it and then maintain it, as the hardware can be costly and if problems arise there is no cloud provider to handle maintenance requests. Although there is a wide range of equipment options in the market, prices can significantly vary depending on the supplier and specifications of such equipment depending on the needs of the desired local physical server and storage capacity. Thus, cloud databases present one of the best solutions for small food companies who are creating new goods but lack the financial capacity to invest in uncertain projects. The prices of the cloud servers can be lower, varying from free trials with limited data capacity (e.g. MongoDB and IBM) to various plans depending on an extensive range of features related to apps, cloud, connection, device management, etc. ThingSpeak, for example, has an academic license of 250 $/year, while the standard version can be more expensive [126]. In other databases, such as Firebase and Ledger, the users pay only for what they use and there are no minimum fees or mandatory service usage, the prices in those cases are $5 and $0.09 for each GB/month, respectively [127,128].

## 4.4 Applications and software – the application and control layer

The software and mobile applications column found in Table 2 refer to all of the tools that researchers used for extracting, analysing, modelling, and visualising the data to ultimately deliver the application layer of their IoT architectures. In general, it was found that the authors used an extensive variety of options.

As data keeps being collected and stored into appropriate databases, for executing continuous monitoring and control of parameters, algorithms or ML techniques can be applied to extract insights, identify patterns or make predictions, among others. Among the ML techniques used in Table 2, the authors chose supervised learning classification and regression algorithms including Naïve Bayes, ID3, XGBoost, multiple linear regression, non-linear regression, CNN-SVM and others to gain further understanding about the collected data. For example, Torres-Sánchez et al. [41] developed a multiple non-linear regression model from temperature sensor data to predict the reduction in shelf life of perishables when temperature conditions varied from the theoretical set-point during transportation along the food supply chain. In other words, the authors used this model to find a correlation between temperature and loss of shelf life. Another algorithm application can be found in the study by Feng et al. [43], which used the combination or hybrid ML algorithm: CNN-SVM (convolutional neural network and support vector machine). The CNN-SVM hybrid is often used to exploit the main advantages of each algorithm, that is, CNN as a powerful tool for feature selection and SVM as an effective classifier. The authors used this technique to evaluate the freshness of salmon during (IoT-enabled) cold storage and classify each salmon sample according to levels of freshness. Aytaç and Korçak [30] tested the accuracy of both Naïve Bayes and decision trees for predicting restaurant demand. In this work, the models were trained on waste bin weight data, incremental sales data, and external events data scraped from the internet and social media which could influence demand. The training data were manually labelled with a service-level indicator. Once training was completed, the model was able to predict the production service level required without any human intervention, meaning arriving customers did not need to wait for food to be produced while minimising the amount of food waste generated due to the product’s short lifetime. In addition, the study also successfully utilised an unsupervised learning approach to perform outlier detection based on k-means clustering analysis.

It was also observed that researchers in the selected studies preferred to employ either Matlab or Python programming language for data analysis. As for the usage preference among these, it was equally split between Matlab (n = 4) and Python (n = 4), the latter including Spyder, MicroPython and Python 2.7. One unique approach is noted by Banga et al. [45] who identifies insect infestation during the storage of legumes using acoustic detection methods. For this approach, the authors use Audacity for signal processing, followed by the Pratt tool for spectrogram signal analysis based on Linear predictive coding.

Additionally, visualisation tools can be utilised to facilitate the interpretation of data, not only by the scientists or IoT engineers that developed the system, but also as part of a user-friendly software or mobile applications, which could also be employed by potential users in the food supply chain such as farmers, producers or distributors, to allow real-time access to the environmental or product conditions. The authors utilised or developed a mixture of real-time visualisation applications on mobile and desktop using various technologies. Of note, the authors mention node.js and Flask for the development of Web-based applications and Java and C# for the development of bespoke offline Windows applications. Off the shelf products like Labview and Matlab's Simulink have also been utilised for visualisation on the application layer, as noted by Ibba et al. [35], Jilani et al. [52], and Bustamante et al. [81]. Android Studio is mentioned to be used for the development of mobile applications.

It is also worth mentioning the service provided by IBM, the IBM Watson IoT Platform (n = 3), which allows users to connect devices via API calls to see live and historical data and create applications within IBM or other clouds. For instance, Morillo et al. [63] used the IBM Watson IoT Platform to collect, process, and visualise the smartphone readings sent to the IBM cloud via 3G or 4G networks of a meal distribution trolley monitoring system in hospital settings [63].

In summary, it was seen that a wide array of ML algorithms, programming languages, visualisation tools and applications were deployed by researchers. While common tools like Python, Matlab, and Labview are recurringly utilised in the articles, each application tends to be unique, perhaps explained by the distinct nature and diversity of the use cases under review. With many different types of produce, supply chain stages, sensing parameters, hardware, communication technologies, etc. being the focus of the research, there is no standard approach to delivering the application layer in a food supply chain IoT system as to date, with a high degree of novelty and experimentation still under development.

# 5. Conclusion

This report has presented an overview of the current state of IoT systems deployed in the food supply chain in order to minimise food waste production. It has identified a number of new themes and research opportunities that can be pursued by future researchers in this field. As previously seen, IoT implementation in food supply chains focuses on high perishability products, i.e. fruits (31.7%), vegetables (15.9%), meat (12.2%) and seafood (9.8%). Although it can be difficult to maintain the microbiological integrity of fresh products, IoT technologies have demonstrated its helpfulness and practical approach to preventing FLW from different food categories. Future studies could expand their research to encompass other food products in order to determine the effects of using real-time monitoring technologies on food waste reduction. In addition, different food supply chain stages can be analysed in future scenarios, as most of the studies concentrated their efforts on the storage (38%) and transportation (37%) stages.

The research has also shown that current sensing technologies seem to be predominantly focused on temperature (81%) and humidity (60%), followed by gas composition/concentration (31%) and light intensity (12%). However, other sensing parameters are also important, and hence future studies can focus on further development of these sensing parameters. In addition, opportunities arising from the integration of spectroscopic and imaging techniques in IoT networks can be exploited. Several of these techniques have been broadly researched for real-time food monitoring applications. Examples include Raman, Near-infrared (NIR), Fourier transform infrared (FTIR), 3D fluorescence and Laser-induced breakdown spectroscopy (LIBS), among others.

Regarding communication transfer, different wireless communication technologies were used, but the most frequently were cellular technologies (25.8%), WiFi (21.5%), Zigbee (11.8%) and RFID (10.8%). It was observed that the suitability of network protocols is greatly influenced by real-world applications and many factors need to be further studied to determine the most appropriate, such as, network reliability, roaming capability, price and installation costs. Regarding data storage and control, a great part of the studies relied on cloud servers and remote databases to store and manage their information. This is mainly due to its advantages in terms of flexibility, scalability and costs, which is highly recommended for small food companies who are creating new goods but lack the financial capacity to invest in new projects.

Overall, the findings demonstrated this technology's enormous promise and successful applications. IoT solutions are expected to influence not only the way food is produced, managed, transported and stored, but also social, environmental, and economic impacts. As a result, IoT systems applied to the food industry are becoming increasingly common in the existing literature. However, similar systematic literature reviews will need to be undertaken focusing on other aspects related to the applications of IoT sensors for reducing FLW in order to gain a complete picture of the domain. These include a review of cloud storage technologies, artificial intelligence (AI) technologies and data analytics technologies.

# 6. References


1. Chauhan, C.; Dhir, A.; Akram, M.U.; Salo, J. Food Loss and Waste in Food Supply Chains. A Systematic Literature Review and Framework Development Approach. *J Clean Prod* 2021, *295*, 126438, doi:10.1016/j.jclepro.2021.126438.
2. Roe, B.E.; Qi, D.; Bender, K.E. Some Issues in the Ethics of Food Waste. *Physiol Behav* 2020, *219*, 112860, doi:10.1016/j.physbeh.2020.112860.
3. Cristóbal, J.; Castellani, V.; Manfredi, S.; Sala, S. Prioritizing and Optimizing Sustainable Measures for Food Waste Prevention and Management. *Waste Management* 2018, *72*, 3–16, doi:10.1016/j.wasman.2017.11.007.
4. Amicarelli, V.; Lagioia, G.; Bux, C. Global Warming Potential of Food Waste through the Life Cycle Assessment: An Analytical Review. *Environ Impact Assess Rev* 2021, *91*, 106677, doi:10.1016/j.eiar.2021.106677.
5. Ishangulyyev, R.; Kim, S.; Lee, S. Understanding Food Loss and Waste—Why Are We Losing and Wasting Food? *Foods* 2019, *8*, 297, doi:10.3390/foods8080297.
6. UN *The 2030 Agenda for Sustainable Development. A/RES/70/1. United Nations.*; 2015;
7. EC Cutting Food Waste with Technology That Keeps Produce Fresh. European Commission. Available online: https://ec.europa.eu/research-and-innovation/en/projects/success-stories/all/cutting-food-waste-technology-keeps-produce-fresh (accessed on 28 June 2021).
8. Mustafa, F.; Andreescu, S. Chemical and Biological Sensors for Food-Quality Monitoring and Smart Packaging. *Foods* 2018, *7*, 168, doi:10.3390/foods7100168.
9. Astill, J.; Dara, R.A.; Campbell, M.; Farber, J.M.; Fraser, E.D.G.; Sharif, S.; Yada, R.Y. Transparency in Food Supply Chains: A Review of Enabling Technology Solutions. *Trends Food Sci Technol* 2019, *91*, 240–247, doi:10.1016/j.tifs.2019.07.024.
10. Jagtap, S.; Rahimifard, S. The Digitisation of Food Manufacturing to Reduce Waste – Case Study of a Ready Meal Factory. *Waste Management* 2019, *87*, 387–397, doi:10.1016/j.wasman.2019.02.017.
11. Bux, C.; Varese, E.; Amicarelli, V.; Lombardi, M. Halal Food Sustainability between Certification and Blockchain: A Review. *Sustainability* 2022, *14*, 2152, doi:10.3390/su14042152.
12. Rana, R.L.; Tricase, C.; de Cesare, L. Blockchain Technology for a Sustainable Agri-Food Supply Chain. *British Food Journal* 2021, *123*, 3471–3485, doi:10.1108/BFJ-09-2020-0832.
13. Majrouhi Sardroud, J. Influence of RFID Technology on Automated Management of Construction Materials and Components. *Scientia Iranica* 2012, *19*, 381–392, doi:10.1016/j.scient.2012.02.023.
14. Irani, Z.; Sharif, A.M.; Lee, H.; Aktas, E.; Topaloğlu, Z.; van't Wout, T.; Huda, S. Managing Food Security through Food Waste and Loss: Small Data to Big Data. *Comput Oper Res* 2018, *98*, 367–383, doi:10.1016/j.cor.2017.10.007.
15. Harvey, J.; Smith, A.; Goulding, J.; Branco Illodo, I. Food Sharing, Redistribution, and Waste Reduction via Mobile Applications: A Social Network Analysis. *Industrial Marketing Management* 2020, *88*, 437–448, doi:10.1016/j.indmarman.2019.02.019.
16. Kamble, S.S.; Gunasekaran, A.; Parekh, H.; Joshi, S. Modeling the Internet of Things Adoption Barriers in Food Retail Supply Chains. *Journal of Retailing and Consumer Services* 2019, *48*, 154–168, doi:10.1016/j.jretconser.2019.02.020.
17. Pavelková, A. Time Temperature Indicators as Devices Intelligent Packaging. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis* 2013, *61*, 245–251, doi:10.11118/actaun201361010245.

18. Syahputri, B.E.; Sucipto, S. Monitoring of Beef Cold Chain to Ensure Quality, Safety, and Halal Using RFID: A Review. *IOP Conf Ser Earth Environ Sci* 2021, *924*, 012001, doi:10.1088/1755-1315/924/1/012001.

19. Cetateanu, A.; Jones, A. How Can GPS Technology Help Us Better Understand Exposure to the Food Environment? A Systematic Review. *SSM Popul Health* 2016, *2*, 196–205, doi:10.1016/j.ssmph.2016.04.001.

20. Nižetić, S.; Šolić, P.; López-de-Ipiña González-de-Artaza, D.; Patrono, L. Internet of Things (IoT): Opportunities, Issues and Challenges towards a Smart and Sustainable Future. *J Clean Prod* 2020, *274*, 122877, doi:10.1016/j.jclepro.2020.122877.

21. Angarita-Zapata, J.S.; Alonso-Vicario, A.; Masegosa, A.D.; Legarda, J. A Taxonomy of Food Supply Chain Problems from a Computational Intelligence Perspective. *Sensors* 2021, *21*, 6910, doi:10.3390/s21206910.

22. FAO *The State of Food Security and Nutrition in the World: Building Resilience for Peace and Food Security. Food and Agriculture Organization of the United Nations. Rome.*; 2017;

23. Tran, B.X.; McIntyre, R.S.; Latkin, C.A.; Phan, H.T.; Vu, G.T.; Nguyen, H.L.T.; Gwee, K.K.; Ho, C.S.H.; Ho, R.C.M. The Current Research Landscape on the Artificial Intelligence Application in the Management of Depressive Disorders: A Bibliometric Analysis. *Int J Environ Res Public Health* 2019, *16*, 2150, doi:10.3390/ijerph16122150.

24. van Eck, N.J.; Waltman, L. Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping. *Scientometrics* 2010, *84*, 523–538, doi:10.1007/s11192-009-0146-3.

25. ENISA Internet of Things Is Transforming the Boundaries between the Digital and Physical World. European Union Agency for Cybersecurity.

26. Zhu, Z.; Ma, R.; Draganic, A.; Orovic, I.; Zhang, X.; Wang, X.; Wang, J. Postharvest Quality Monitoring and Cold Chain Management of Fresh Garlic Scapes Based on a Wireless Multi-sensors System. *J Food Process Eng* 2021, doi:10.1111/jfpe.13918.

27. Afreen, H.; Bajwa, I.S. An IoT-Based Real-Time Intelligent Monitoring and Notification System of Cold Storage. *IEEE Access* 2021, *9*, 38236–38253, doi:10.1109/ACCESS.2021.3056672.

28. Torres-Sanchez, R.; Zafra, M.T.M.; Soto-Valles, F.; Jiménez-Buendía, M.; Toledo-Moreo, A.; Artés-Hernández, F. Design of a Distributed Wireless Sensor Platform for Monitoring and Real-Time Communication of the Environmental Variables during the Supply Chain of Perishable Commodities. *Applied Sciences* 2021, *11*, 6183, doi:10.3390/app11136183.

29. Siddiqui, M.; Akther, F.; Rahman, G.M.E.; Elahi, M.M.; Mostafa, R.; Wahid, K.A. Dimensioning of Wide-Area Alternate Wetting and Drying (AWD) System for IoT-Based Automation. *Sensors* 2021, *21*, 6040, doi:10.3390/s21186040.

30. Aytaç, K.; Korçak, Ö. IoT Based Intelligence for Proactive Waste Management in Quick Service Restaurants. *J Clean Prod* 2021, *284*, 125401, doi:10.1016/j.jclepro.2020.125401.

31. Zheng, M.; Zhang, S.; Zhang, Y.; Hu, B. Optimization of Water Microbial Concentration Monitoring System Based on Internet of Things. *Complexity* 2021, *2021*, 1–11, doi:10.1155/2021/5154922.

32. Li, G. Development of Cold Chain Logistics Transportation System Based on 5G Network and Internet of Things System. *Microprocess Microsyst* 2021, *80*, 103565, doi:10.1016/j.micpro.2020.103565.

33. Nair, K.; Sekhani, B.; Shah, K.; Karamchandani, S. Expiry Prediction and Reducing Food Wastage Using IoT and ML. *International journal of electrical and computer engineering systems* 2021, *12*, 155–162, doi:10.32985/ijeces.12.3.4.

34. Sharif, A.; Abbasi, Q.H.; Arshad, K.; Ansari, S.; Ali, M.Z.; Kaur, J.; Abbas, H.T.; Imran, M.A. Machine Learning Enabled Food Contamination Detection Using RFID and Internet of Things System. *Journal of Sensor and Actuator Networks* 2021, *10*, 63, doi:10.3390/jsan10040063.

35. Ibba, P.; Falco, A.; Abera, B.D.; Cantarella, G.; Petti, L.; Lugli, P. Bio-Impedance and Circuit Parameters: An Analysis for Tracking Fruit Ripening. *Postharvest Biol Technol* 2020, *159*, 110978, doi:10.1016/j.postharvbio.2019.110978.

36. Catania, P.; Gaglio, R.; Orlando, S.; Settanni, L.; Vallone, M. Design and Implementation of a Smart System to Control Aromatic Herb Dehydration Process. *Agriculture* 2020, *10*, 332, doi:10.3390/agriculture10080332.

37. Lu, C.-Y.; Chen, F.-H.; Hsu, W.-C.; Lee, L.-W.; Su, T.-J. Development of Smart Refrigerator Based on Message Queuing Telemetry Transport. *Sensors and Materials* 2020, *32*, 1899, doi:10.18494/SAM.2020.2617.

38. Wang, X.; Li, X.; Fu, D.; Vidrih, R.; Zhang, X. Ethylene Sensor-Enabled Dynamic Monitoring and Multi-Strategies Control for Quality Management of Fruit Cold Chain Logistics. *Sensors* 2020, *20*, 5830, doi:10.3390/s20205830.

39. Feng, H.; Wang, W.; Chen, B.; Zhang, X. Evaluation on Frozen Shellfish Quality by Blockchain Based Multi-Sensors Monitoring and SVM Algorithm During Cold Storage. *IEEE Access* 2020, *8*, 54361–54370, doi:10.1109/ACCESS.2020.2977723.

40. Zhang, X.; Wang, X.; Xing, S.; Ma, Y.; Wang, X. Multi-Sensors Enabled Dynamic Monitoring and Quality Assessment System (DMQAS) of Sweet Cherry in Express Logistics. *Foods* 2020, *9*, 602, doi:10.3390/foods9050602.

41. Torres-Sánchez, R.; Martínez-Zafra, M.T.; Castillejo, N.; Guillamón-Frutos, A.; Artés-Hernández, F. Real-Time Monitoring System for Shelf Life Estimation of Fruit and Vegetables. *Sensors* 2020, *20*, 1860, doi:10.3390/s20071860.

42. Urbano, O.; Perles, A.; Pedraza, C.; Rubio-Arraez, S.; Castelló, M.L.; Ortola, M.D.; Mercado, R. Cost-Effective Implementation of a Temperature Traceability System Based on Smart RFID Tags and IoT Services. *Sensors* 2020, *20*, 1163, doi:10.3390/s20041163.

43. Feng, H.; Zhang, M.; Liu, P.; Liu, Y.; Zhang, X. Evaluation of IoT-Enabled Monitoring and Electronic Nose Spoilage Detection for Salmon Freshness During Cold Storage. *Foods* 2020, *9*, 1579, doi:10.3390/foods9111579.

44. Markovic, M.; Jacobs, N.; Dryja, K.; Edwards, P.; Strachan, N.J.C. Integrating Internet of Things, Provenance, and Blockchain to Enhance Trust in Last Mile Food Deliveries. *Front Sustain Food Syst* 2020, *4*, doi:10.3389/fsufs.2020.563424.

45. Ramírez-Faz, J.; Fernández-Ahumada, L.M.; Fernández-Ahumada, E.; López-Luque, R. Monitoring of Temperature in Retail Refrigerated Cabinets Applying IoT Over Open-Source Hardware and Software. *Sensors* 2020, *20*, 846, doi:10.3390/s20030846.

46. Seman, M.T.A.; Abdullah, M.N.; Ishak, M.K. *Monitoring Temperature, Humidity and Controlling System in Industrial Fixed Room Storage Based on IoT*; 2020; Vol. 15;.

47. Alfian, G.; Syafrudin, M.; Farooq, U.; Ma'arif, M.R.; Syaekhoni, M.A.; Fitriyani, N.L.; Lee, J.; Rhee, J. Improving Efficiency of RFID-Based Traceability System for Perishable Food by Utilizing IoT Sensors and Machine Learning Model. *Food Control* 2020, *110*, 107016, doi:10.1016/j.foodcont.2019.107016.

48. Banga, Km.S.; Kotwaliwale, N.; Mohapatra, D.; Giri, S.K.; Babu, V.B. Bioacoustic Detection of Callosobruchus Chinensis and Callosobruchus Maculatus in Bulk Stored Chickpea (Cicer Arietinum) and Green Gram (Vigna Radiata). *Food Control* 2019, *104*, 278–287, doi:10.1016/j.foodcont.2019.02.026.

49. Feng, H.; Chen, J.; Zhou, W.; Rungsardthong, V.; Zhang, X. Modeling and Evaluation on WSN-Enabled and Knowledge-Based HACCP Quality Control for Frozen Shellfish Cold Chain. *Food Control* 2019, *98*, 348–358, doi:10.1016/j.foodcont.2018.11.050.

50. Jara, P.B.T.; Rivera, J.J.A.; Merino, C.E.B.; Silva, E.V.; Farfán, G.A. Thermal Behavior of a Refrigerated Vehicle: Process Simulation. *International Journal of Refrigeration* 2019, *100*, 124–130, doi:10.1016/j.ijrefrig.2018.12.013.

51. Baire, M.; Melis, A.; Lodi, M.B.; Tuveri, P.; Dachena, C.; Simone, M.; Fanti, A.; Fumera, G.; Pisanu, T.; Mazzarella, G. A Wireless Sensors Network for Monitoring the Carasau Bread Manufacturing Process. *Electronics (Basel)* 2019, *8*, 1541, doi:10.3390/electronics8121541.

52. Jilani, M.T.; Rehman, M.Z.U.; Khan, A.M.; Chughtai, O.; Abbas, M.A.; Khan, M.T. An Implementation of IoT-Based Microwave Sensing System for the Evaluation of Tissues Moisture. *Microelectronics J* 2019, *88*, 117–127, doi:10.1016/j.mejo.2018.03.006.

53. Mondal, S.; Wijewardena, K.P.; Karuppuswami, S.; Kriti, N.; Kumar, D.; Chahal, P. Blockchain Inspired RFID-Based Information Architecture for Food Supply Chain. *IEEE Internet Things J* 2019, *6*, 5803–5813, doi:10.1109/JIOT.2019.2907658.

54. Lazaro, A.; Boada, M.; Villarino, R.; Girbau, D. Color Measurement and Analysis of Fruit with a Battery-Less NFC Sensor. *Sensors* 2019, *19*, 1741, doi:10.3390/s19071741.

55. Tsang, Y.P.; Choy, K.L.; Wu, C.H.; Ho, G.T.S.; Lam, H.Y. Blockchain-Driven IoT for Food Traceability With an Integrated Consensus Mechanism. *IEEE Access* 2019, *7*, 129000–129017, doi:10.1109/ACCESS.2019.2940227.

56. Popa, A.; Hnatiuc, M.; Paun, M.; Geman, O.; Hemanth, D.; Dorcea, D.; Son, L.; Ghita, S. An Intelligent IoT-Based Food Quality Monitoring Approach Using Low-Cost Sensors. *Symmetry (Basel)* 2019, *11*, 374, doi:10.3390/sym11030374.

57. Tsang, Y.P.; Choy, K.L.; Wu, C.H.; Ho, G.T.S.; Lam, C.H.Y.; Koo, P.S. An Internet of Things (IoT)-Based Risk Monitoring System for Managing Cold Supply Chain Risks. *Industrial Management & Data Systems* 2018, *118*, 1432–1462, doi:10.1108/IMDS-09-2017-0384.

58. Tsang, Y.P.; Choy, K.L.; Wu, C.H.; Ho, G.T.S.; Lam, H.Y.; Tang, V. An Intelligent Model for Assuring Food Quality in Managing a Multi-Temperature Food Distribution Centre. *Food Control* 2018, *90*, 81–97, doi:10.1016/j.foodcont.2018.02.030.

59. Wen, Z.; Hu, S.; de Clercq, D.; Beck, M.B.; Zhang, H.; Zhang, H.; Fei, F.; Liu, J. Design, Implementation, and Evaluation of an Internet of Things (IoT) Network System for Restaurant Food Waste Management. *Waste Management* 2018, *73*, 26–38, doi:10.1016/j.wasman.2017.11.054.

60. Wang, X.; Li, L.; Moga, L.M.; Zhang, X.; Zhang, Y. Development and Evaluation on a Wireless Multi-Sensors System for Fresh-Cut Branches of the North American Holly Cold Chain. *Comput Electron Agric* 2018, *148*, 132–141, doi:10.1016/j.compag.2018.03.011.

61. Wang, X.; Fu, D.; Fruk, G.; Chen, E.; Zhang, X. Improving Quality Control and Transparency in Honey Peach Export Chain by a Multi-Sensors-Managed Traceability System. *Food Control* 2018, *88*, 169–180, doi:10.1016/j.foodcont.2018.01.008.

62. de Venuto, D.; Mezzina, G. Spatio-Temporal Optimization of Perishable Goods' Shelf Life by a Pro-Active WSN-Based Architecture. *Sensors* 2018, *18*, 2126, doi:10.3390/s18072126.

63. Morillo, P.; Orduña, J.M.; Fernández, M.; García-Pereira, I. Comparison of WSN and IoT Approaches for a Real-Time Monitoring System of Meal Distribution Trolleys: A Case Study. *Future Generation Computer Systems* 2018, *87*, 242–250, doi:10.1016/j.future.2018.01.032.

64. Chaudhari, M.P. Predictive Analytics for Anomaly Detection in Internet of Things Enabled Smart Cold Storage Warehousing. *HELIX* 2018, *8*, 3941–3945, doi:10.29042/2018-3941-3945.

65. Tervonen, J. Experiment of the Quality Control of Vegetable Storage Based on the Internet-of-Things. *Procedia Comput Sci* 2018, *130*, 440–447, doi:10.1016/j.procs.2018.04.065.

66. Jedermann, R.; Praeger, U.; Lang, W. Challenges and Opportunities in Remote Monitoring of Perishable Products. *Food Packag Shelf Life* 2017, *14*, 18–25, doi:10.1016/j.fpsl.2017.08.006.

67. Xiao, X.; He, Q.; Li, Z.; Antoce, A.O.; Zhang, X. Improving Traceability and Transparency of Table Grapes Cold Chain Logistics by Integrating WSN and Correlation Analysis. *Food Control* 2017, *73*, 1556–1563, doi:10.1016/j.foodcont.2016.11.019.

68. Tsang, Y.; Choy, K.; Wu, C.; Ho, G.; Lam, H.; Koo, P. An IoT-Based Cargo Monitoring System for Enhancing Operational Effectiveness under a Cold Chain Environment. *International Journal of Engineering Business Management* 2017, *9*, 184797901774906, doi:10.1177/1847979017749063.

69. Alfian, G.; Syafrudin, M.; Rhee, J. Real-Time Monitoring System Using Smartphone-Based Sensors and NoSQL Database for Perishable Supply Chain. *Sustainability* 2017, *9*, 2073, doi:10.3390/su9112073.

70. Musa, Z.; Vidyasankar, K. A Fog Computing Framework for Blackberry Supply Chain Management. *Procedia Comput Sci* 2017, *113*, 178–185, doi:10.1016/j.procs.2017.08.338.

71. Seo, S.-M.; Kim, S.-W.; Jeon, J.-W.; Kim, J.-H.; Kim, H.-S.; Cho, J.-H.; Lee, W.-H.; Paek, S.-H. Food Contamination Monitoring via Internet of Things, Exemplified by Using Pocket-Sized Immunosensor as Terminal Unit. *Sens Actuators B Chem* 2016, *233*, 148–156, doi:10.1016/j.snb.2016.04.061.

72. Xiao, X.; He, Q.; Fu, Z.; Xu, M.; Zhang, X. Applying CS and WSN Methods for Improving Efficiency of Frozen and Chilled Aquatic Products Monitoring System in Cold Chain Logistics. *Food Control* 2016, *60*, 656–666, doi:10.1016/j.foodcont.2015.09.012.

73. Shih, C.-W.; Wang, C.-H. Integrating Wireless Sensor Networks with Statistical Quality Control to Develop a Cold Chain System in Food Industries. *Comput Stand Interfaces* 2016, *45*, 62–78, doi:10.1016/j.csi.2015.12.004.

74. Thakur, M.; Forås, E. EPCIS Based Online Temperature Monitoring and Traceability in a Cold Meat Chain. *Comput Electron Agric* 2015, *117*, 22–30, doi:10.1016/j.compag.2015.07.006.

75. Badia-Melis, R.; Ruiz-Garcia, L.; Garcia-Hierro, J.; Villalba, J. Refrigerated Fruit Storage Monitoring Combining Two Different Wireless Sensing Technologies: RFID and WSN. *Sensors* 2015, *15*, 4781–4795, doi:10.3390/s150304781.

76. Chen, Y.-Y.; Wang, Y.-J.; Jan, J.-K. A Novel Deployment of Smart Cold Chain System Using 2G-RFID-Sys. *J Food Eng* 2014, *141*, 113–121, doi:10.1016/j.jfoodeng.2014.05.014.

77. Aung, M.M.; Chang, Y.S. Temperature Management for the Quality Assurance of a Perishable Food Supply Chain. *Food Control* 2014, *40*, 198–207, doi:10.1016/j.foodcont.2013.11.016.

78. Eom, K.-H.; Hyun, K.-H.; Lin, S.; Kim, J.-W. The Meat Freshness Monitoring System Using the Smart RFID Tag. *Int J Distrib Sens Netw* 2014, *10*, 591812, doi:10.1155/2014/591812.

79. Smiljkovikj, K.; Gavrilovska, L. SmartWine: Intelligent End-to-End Cloud-Based Monitoring System. *Wirel Pers Commun* 2014, *78*, 1777–1788, doi:10.1007/s11277-014-1905-x.

80. Hafliðason, T.; Ólafsdóttir, G.; Bogason, S.; Stefánsson, G. Criteria for Temperature Alerts in Cod Supply Chains. *International Journal of Physical Distribution & Logistics Management* 2012, *42*, 355–371, doi:10.1108/09600031211231335.

81. Bustamante, E.; Guijarro, E.; García-Diego, F.-J.; Balasch, S.; Hospitaler, A.; Torres, A.G. Multisensor System for Isotemporal Measurements to Assess Indoor Climatic Conditions in Poultry Farms. *Sensors* 2012, *12*, 5752–5774, doi:10.3390/s120505752.

82. Faccio, M.; Persona, A.; Zanin, G. Waste Collection Multi Objective Model with Real Time Traceability Data. *Waste Management* 2011, *31*, 2391–2405, doi:10.1016/j.wasman.2011.07.005.

83. Wang, L.; Kwok, S.K.; Ip, W.H. A Radio Frequency Identification and Sensor-Based System for the Transportation of Food. *J Food Eng* 2010, *101*, 120–129, doi:10.1016/j.jfoodeng.2010.06.020.

84. Ruiz-Garcia, L.; Barreiro, P.; Robla, J.I. Performance of ZigBee-Based Wireless Sensor Nodes for Real-Time Monitoring of Fruit Logistics. *J Food Eng* 2008, *87*, 405–415, doi:10.1016/j.jfoodeng.2007.12.033.

85. Dilucia, F.; Lacivita, V.; Conte, A.; del Nobile, M.A. Sustainable Use of Fruit and Vegetable By-Products to Enhance Food Packaging Performance. *Foods* 2020, *9*, 857, doi:10.3390/foods9070857.

86. Iulietto, M.F.; Sechi, P.; Borgogni, E.; Cenci-Goga, B.T. Meat Spoilage: A Critical Review of a Neglected Alteration Due to Ropy Slime Producing Bacteria. *Ital J Anim Sci* 2015, *14*, 4011, doi:10.4081/ijas.2015.4011.

87. Chaillou, S.; Chaulot-Talmon, A.; Caekebeke, H.; Cardinal, M.; Christieans, S.; Denis, C.; Hélène Desmonts, M.; Dousset, X.; Feurer, C.; Hamon, E.; et al. Origin and Ecological Selection of Core and Food-Specific Bacterial Communities Associated with Meat and Seafood Spoilage. *ISME J* 2015, *9*, 1105–1118, doi:10.1038/ismej.2014.202.

88. Martínez, Z.N.; Menacho P., Z.; Pachón-Ariza, F. Food Loss in a Hungry World, a Problem? *Agron Colomb* 2014, *32*, 283–293, doi:10.15446/agron.colomb.v32n2.43470.

89. McKellar, R.C.; LeBlanc, D.I.; Rodríguez, F.P.; Delaquis, P. Comparative Simulation of Escherichia Coli O157:H7 Behaviour in Packaged Fresh-Cut Lettuce Distributed in a Typical Canadian Supply Chain in the Summer and Winter. *Food Control* 2014, *35*, 192–199, doi:10.1016/j.foodcont.2013.06.002.

90. Skawińska, E.; Zalewski, R.I. Economic Impact of Temperature Control during Food Transportation—A COVID-19 Perspective. *Foods* 2022, *11*, 467, doi:10.3390/foods11030467.

91. FAO *Fruit and Vegetables – Opportunities and Challenges for Small-Scale Sustainable Farming. Food and Agriculture Organization of the United Nations (FAO) and Agricultural Research Centre for International Development (CIRAD). Rome, Italy.*; 2021;

92. FAO *The State of World Fisheries and Aquaculture 2022. Towards Blue Transformation. Food and Agriculture Organization of the United Nations. Rome, Italy.*; 2022;

93. GSMA *Mass Deployments of IoT Solutions Transforming China. Groupe Speciale Mobile Association.*; London, UK., 2019;

94. Global Times China Rolls out 1.6 Million 5G Base Stations, All Rural Villages Having Access to Broadband. .

95. ISC *China Internet Development Report. Internet Society of China. Beijing, China.*; 2021;

96. Feng, Y.; Marek, C.; Tosun, J. Fighting Food Waste by Law: Making Sense of the Chinese Approach. *J Consum Policy (Dordr)* 2022, *45*, 457–479, doi:10.1007/s10603-022-09519-2.

97. Peel, M.C.; Finlayson, B.L.; McMahon, T.A. Updated World Map of the Köppen-Geiger Climate Classification. *Hydrol Earth Syst Sci* 2007, *11*, 1633–1644, doi:10.5194/hess-11-1633-2007.

98. Robertson, G.P.; Grandy, A.S. Soil System Management in Temperate Regions. In *Biological approaches to sustainable soil systems*; Uphoff, N., Ball, A.S., Fernandes, E., Herren, H., Husson, O., Laing, M., Palm, C., Pretty, J., Sanchez, P., Snanginga, N., Thies, J., Eds.; CRC Press, Boca Raton, Florida, USA., 2006; pp. 27–39.

99. Rosenzweig, C.; Liverman, D. Predicted Effects of Climate Change on Agriculture: A Comparison of Temperate and Tropical Regions. In *Global climate change: Implications, challenges, and mitigation measures*; Majumdar, S.K., Ed.; PA: The Pennsylvania Academy of Sciences., 1992; pp. 61–342.

100. Ferdaous, Z.; Stefan, H.; Sanchez, G.M. What Drives Firm Profitability? A Multilevel Approach to the Spanish Agri-Food Sector. In Proceedings of the 56th Annual Conference of the German Association of Agricultural Economists (GEWISOLA), Bonn, Germany, September 28-30.; 2016.

101. McGrath, M.J.; Scanaill, C.N. Sensing and Sensor Fundamentals. In *Sensor Technologies*; Apress: Berkeley, CA, 2013; pp. 15–50.

102. Salinas Alvarez, C.; Sierra–Sosa, D.; Garcia–Zapirain, B.; Yoder–Himes, D.; Elmaghraby, A. Detection of Volatile Compounds Emitted by Bacteria in Wounds Using Gas Sensors. *Sensors* 2019, *19*, 1523, doi:10.3390/s19071523.
103. Wazwaz, A.; Amin, K. Error Rate Control in Humidity and Temperature Sensors Using IoT and ThingSpeak. In Proceedings of the Proceedings of the 2020 10th International Conference on Information Communication and Management; ACM: New York, NY, USA, August 12 2020; pp. 71–75.
104. Pandey, N.; Tiwari, A.; Sharma, S.; Teja, P.S.; Jaiswal, R.; Kumar, A. Sustainable Farming for Agronomy Upliment Using IoT. *International Journal of Engineering Applied Sciences and Technology* 2019, *4*.
105. MBED Grove Temperature Humidity Sensors.
106. Mahardika, P.S.; Gunawan, A.A.N. Modeling of Water Temperature in Evaporation Pot with 7 Ds18b20 Sensors Based on Atmega328 Microcontroller. *Linguistics and Culture Review* 2022, *6*, 184–193, doi:10.21744/lingcure.v6nS3.2123.
107. Marszałek, K.; Woźniak, Ł.; Barba, F.J.; Skąpska, S.; Lorenzo, J.M.; Zambon, A.; Spilimbergo, S. Enzymatic, Physicochemical, Nutritional and Phytochemical Profile Changes of Apple (Golden Delicious L.) Juice under Supercritical Carbon Dioxide and Long-Term Cold Storage. *Food Chem* 2018, *268*, 279–286, doi:10.1016/j.foodchem.2018.06.109.
108. Xiong, Y.; Meng, Q.; Gao, J.; Tang, X.; Zhang, H. Effects of Relative Humidity on Animal Health and Welfare. *J Integr Agric* 2017, *16*, 1653–1658, doi:10.1016/S2095-3119(16)61532-0.
109. Jagtap, S.; Duong, L.; Trollman, H.; Bader, F.; Garcia-Garcia, G.; Skouteris, G.; Li, J.; Pathare, P.; Martindale, W.; Swainson, M.; et al. IoT Technologies in the Food Supply Chain. In *Food Technology Disruptions*; Elsevier, 2021; pp. 175–211.
110. Hodara, H.; Skaljo, E. From 1G to 5G. *Fiber and Integrated Optics* 2021, *40*, 85–183, doi:10.1080/01468030.2021.1919358.
111. Costa, C.; Antonucci, F.; Pallottino, F.; Aguzzi, J.; Sarriá, D.; Menesatti, P. A Review on Agri-Food Supply Chain Traceability by Means of RFID Technology. *Food Bioproc Tech* 2013, *6*, 353–366, doi:10.1007/s11947-012-0958-7.
112. Shorey, R.; Miller, B.A. The Bluetooth Technology: Merits and Limitations. In Proceedings of the IEEE International Conference on Personal Wireless Communications. ; IEEE, 2000; pp. 80–84.
113. Abd-El-Barr, M.I.; Youssef, M.A.M.; Al-Otaibi, M.M. Wireless Sensor Networks - Part I: Topology and Design Issues. In Proceedings of the Canadian Conference on Electrical and Computer Engineering.; IEEE, 2005; pp. 1165–1168.
114. Carrasco, A.; Alcaraz, F.; Barbancho, J.; Larios, D.F.; Luis Sevillano, J. Securing a Wireless Sensor Network for Human Tracking: A Review of Solutions. *International Journal of Communication Systems* 2014, *27*, 4384–4406, doi:10.1002/dac.2621.
115. Kazeem, O.O.; Akintade, O.O.; Kehinde, L.O. Comparative Study of Communication Interfaces for Sensors and Actuators in the Cloud of Internet of Things. *International Journal of Internet of Things* 2017, *6*.
116. Singh, R.; Singh, P.; Yadav, K. Wireless Communications Enlargement: A Review of Advancement in Technologies. *International Journal of Current Engineering and Technology* 2014, *4*.
117. Lee, J.-S.; Su, Y.-W.; Shen, C.-C. A Comparative Study of Wireless Protocols: Bluetooth, UWB, ZigBee, and Wi-Fi. In Proceedings of the IECON 2007 - 33rd Annual Conference of the IEEE Industrial Electronics Society; IEEE, 2007; pp. 46–51.

118. Lee, J.-S.; Chuang, C.-C.; Shen, C.-C. Applications of Short-Range Wireless Technologies to Industrial Automation: A ZigBee Approach. In Proceedings of the 2009 Fifth Advanced International Conference on Telecommunications; IEEE, 2009; pp. 15–20.
119. Misra, N.N.; Dixit, Y.; Al-Mallahi, A.; Bhullar, M.S.; Upadhyay, R.; Martynenko, A. IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry. *IEEE Internet Things J* 2022, *9*, 6305–6324, doi:10.1109/JIOT.2020.2998584.
120. Bjeladinovic, S.; Marjanovic, Z.; Babarogic, S. A Proposal of Architecture for Integration and Uniform Use of Hybrid SQL/NoSQL Database Components. *Journal of Systems and Software* 2020, *168*, 110633, doi:10.1016/j.jss.2020.110633.
121. Rai, R.; Chettri, P. NoSQL Hands On. In; 2018; pp. 157–277.
122. Vaclavova, A.; Kebisek, M. Comparison of Various NoSQL Databases for Unstructured Industrial Data. In; 2020; pp. 921–930.
123. Liu, W. Research on Cloud Computing Security Problem and Strategy. In Proceedings of the 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet); IEEE, April 2012; pp. 1216–1219.
124. Avram, M.G. Advantages and Challenges of Adopting Cloud Computing from an Enterprise Perspective. *Procedia Technology* 2014, *12*, 529–534, doi:10.1016/j.protcy.2013.12.525.
125. Ghobadi, A.; Karimi, R.; Heidari, F.; Samadi, M. Cloud Computing, Reliability and Security Issue. In Proceedings of the 16th International Conference on Advanced Communication Technology; Global IT Research Institute (GIRI), February 2014; pp. 504–511.
126. Thingspeak License Options.
127. Amazon Amazon Quantum Ledger Database (QLDB) Pricing.
128. Firebase Pricing Plans.