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Special Issue Reprint

New Multidisciplinary Approaches for Reducing Food Waste in Agribusiness Supply Chains

Edited by
Ramakrishnan Ramanathan, Yanqing Duan, Joan Condell, Usha Ramanathan and Tahmina Ajmal

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Tahmina Ajmal

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Editors

Ramakrishnan Ramanathan
Department of Management
College of Business Administration
University of Sharjah
Sharjah
United Arab Emirates

Yanqing Duan
Business School
University of Bedfordshie
Luton
United Kingdom

Joan Condell
School of Computing, Eng & Intel. Sys
Ulster University
Londonderry
United Kingdom

Usha Ramanathan
Department of Management
College of Business Administration
University of Sharjah
Sharjah
United Arab Emirates

Tahmina Ajmal
School of Computer Science and Technology
University of Bedfordshire
Luton
United Kingdom

Editorial Office
MDPI
St. Alban-Anlage 66
4052 Basel, Switzerland

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About the Editors

Ramakrishnan Ramanathan

Professor Ramakrishnan (Ram) Ramanathan is a Professor at the College of Business Administration, University of Sharjah in the United Arab Emirates. He is a visiting professor at Essex Business School, the University of Essex, Colchester, UK. In the past, he has worked and taught in several countries, including the UK, Finland, the Netherlands, Oman and India. His research interests include operations management, supply chains, and the use of Big Data, Internet of Things and Blockchain technologies for productivity improvement in enterprises and for social causes. He works extensively on modelling using techniques such as optimisation, decision analysis, data envelopment analysis and the analytic hierarchy process. Ram has successfully completed more than 48 research projects globally with than £8 million in funding. Ram is on the editorial boards of several journals and in the technical/advisory committees of several international conferences in his field. He was a member of ESRC Peer Review College in the UK and reviews applications submitted to various funding bodies. He has produced six books, more than 160 research publications in journals and more than 210 conference presentations. His research articles have appeared in many prestigious, internationally refereed journals.

Yanqing Duan

Yanqing (Yan) Duan (BSc, MSc, PhD, SFHEA) is a full Professor of Information Systems and Director of Business and Management Research institutes (BMRI) at the University of Bedfordshire Business School. Prof. Duan is also the founder and leader of Business and Information Systems Research Centre (BISC) in BMRI. Her principal research interest is the applications of emerging ICTs, such as the following: AI, Big Data, IoT and analytics, and their impact on organisational performance, decision-making, and sustainable agrifood supply chains. She is a regular expert evaluator for various major funding bodies, including EU H2020 and Horizon Europe. Professor Duan has led and participated in many research projects on digital transformation and digital agriculture and aquaculture in collaboration with international, European, and UK partners. She has received many research grants from various funding sources, such as the following: European Commission, Innovate UK, UK Department For International Development (DFID), BBSRC, JISC, and the British Council. Prof Duan is a regular keynote speaker on the topics related to the use and impact of emerging digital technologies, especially AI for decision-making. She has published over 270 peer-reviewed articles including papers in the *European Journal of Operational Research*, *European Journal Information Systems*, *European Journal of Marketing*, *IEEE transaction on Engineering Management*, *Information & Management*, *The Information Society*, *Journal of Business Research*, *Industrial Marketing Management*, *Technovation*, and *Information Technology and People*.

Joan Condell

Professor Joan Condell, Professor of Intelligent Technologies at Ulster University, leads the Human-Centred Computing team focusing on data analytics, AI and IoT sensors for applied research, including industrial applications. She manages a team of PhD researchers and Research Associates/Fellows across multiple national, EU and commercial projects (104 projects led in her career to date). Professor Condell has published over 250 papers and actively secured grants from external sources with a total project value over £56M. Professor Condell has considerable commercial experience; she is CEO of a spinout company, ActionSense Ltd., and exited a previous spinout company (HidInImage Ltd).

She has numerous patents filed in UK and US and completed trials with key industrial players with a range of technologies. Joan has won Innovation and Enterprise awards for commercialisation work for creativity and bio-entrepreneurship.

Usha Ramanathan

Usha Ramanathan is a Professor at the College of Business Administration, University of Sharjah (UoS) in the United Arab Emirates. Before joining UoS, Usha worked in Nottingham Trent University as the Professor of sustainability and supply chains. She held academic roles in other Universities in the UK, Oman and India. She obtained her PhD from the University of Nottingham, UK. Usha's research interest lies in the areas of sustainability, supply chain operations, data analytics, customer satisfaction, service performance and technology diffusion. Usha has been successful in obtaining research funding from British Council, British Academy, GCRF and European fundings. She widely published in top-ranked journals, including the *International Journal of Production economics*, *International Journal of Operations and Production Management*, *Omega*, *IEEE Transactions on Engineering Management*, *Technology Forecasting and Social Change*, *Expert Systems with Applications*, and *Journal of Cleaner Production*.

Tahmina Ajmal

Dr. Tahmina Ajmal is an associate professor in Engineering at the University of Bedfordshire with a background in electronics, sensors, and data analytics. She is actively involved in researching various aspects of electronic engineering, but her focus has been on sustainable digital technology for society and sustainability. Her research focus is on the application of sensors and data analytics in novel applications. As a result, she is increasingly working with *Social Sciences* on topics regarding sustainable digital transformation for society and businesses. Some of her recent projects are in precision aquaculture and reducing food waste in supply chains. Her recent projects include Innovate UK/BBSRC project (ADPAC. Aquaculture 4.0—Advancing Digital Precision Aquaculture in China, 2019); Global Challenges Research Funded (GCRF) project (REDIA - Developing a Resilience framework using Digital Innovations for the Aquaculture industry in South Africa); Interreg North-West Europe project (REAMIT Improving Resource Efficiency of Agribusiness supply chains by Minimising waste using Big Data and Internet of Things sensors (2019–2023)) and Insight – Affordable Robotics for Sustainable Agriculture. The impact of her research can be seen through her interdisciplinary output, including research publications in high-quality journals and research collaborations across the world.

Preface

This reprint is a collection of research articles that highlight the achievements of the team of the European project called REAMIT. REAMIT was funded by Interreg North-West Europe and ERDF. The term REAMIT stands for "Improving Resource Efficiency of Agribusiness supply chains by Minimising waste using Big Data and Internet of Things sensors." The main aim of the REAMIT project was to reduce food waste in agrifood supply chains by using the power of modern, digital technologies (e.g., the Internet of Things (IoT), sensors, big data, cloud computing and analytics). The chapters in this reprint provide detailed information of the activities of the project team.

The chapters of this reprint were published as articles in the Special Issue titled "New Multidisciplinary Approaches for Reducing Food Waste in Agribusiness Supply Chains" published in the journal *Sustainability*. For ease of readability and flow, the book is divided into four distinct parts.

In Part 1, the project members provided a comprehensive review of the existing literature. Part 2 is devoted to the in-depth discussions of the development, adaptation, and applications of these technologies for specific food companies. While the project team worked with a number of food companies including human milk, fresh vegetables and fruits, meat production, this part discusses four different applications.

Part 3 presents a detailed analysis of our case studies. A general life-cycle analysis tool for implementing technology for reducing food waste (REAMIT-type activities) is presented in Chapter 7. A specific application of this tool for the case study on a human milk bank is presented in Chapter 8. In Chapter 9, we developed a novel mathematical programming model to identify the conditions when food businesses will prefer the use of modern technologies for helping to reduce food waste.

The final part, Part 4, is devoted to summarising learnings from the project and developing some policy-oriented guidelines. Chapter 10 reviews the current state of corporate reporting guidelines for reporting on food waste. Chapter 11 presents the important leanings from the REAMIT project on the motivations for food companies in reducing waste and the associated challenges. Business models are discussed, and some policy guidelines were developed.

We gratefully acknowledge the generous funding received from the Interreg North-West Europe for carrying out our activities. The content of Chapter 10 was funded additional funding received from the University of Essex. We believe that the reprint and individual chapters will be of interest to a wide and various audience and will kindle interest in food companies, technology companies, business support organisations, policy-makers and members of the academic community in finding ways to reduce food waste with and without the use of technology.

Ramakrishnan Ramanathan, Yanqing Duan, Joan Condell, Usha Ramanathan, and Tahmina Ajmal

Editors

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Review

A Systematic Review of Real-Time Monitoring Technologies and Its Potential Application to Reduce Food Loss and Waste: Key Elements of Food Supply Chains and IoT Technologies

Tamíris Pacheco da Costa [1,*], James Gillespie [2], Xavier Cama-Moncunill [1], Shane Ward [1], Joan Condell [2], Ramakrishnan Ramanathan [3] and Fionnuala Murphy [1]

[1] School of Biosystems & Food Engineering, University College Dublin, Agriculture Building, UCD Belfield, D04 V1W8 Dublin, Ireland
[2] School of Computing, Engineering and Intelligent Systems, Magee Campus, Ulster University, Northland Road, Londonderry BT48 7JL, UK
[3] Essex Business School, Southend Campus, University of Essex, Elmer Approach, Southend-on-Sea, Essex SS1 1LW, UK
* Correspondence: tamiris.dacosta@ucd.ie

Abstract: 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 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 were 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.

Keywords: food loss and waste; IoT technologies; real-time; sensors; food supply chains

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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 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 magnitude of FLW's cost to Earth's resources, food waste carbon footprint has been estimated at 3.3 Gt of CO2-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?

2. Materials and Methods

2.1. Research Methodology

This section presents the systematic literature review methodology of the applications of real-time monitoring technologies for reducing FLW in different stages of the food supply chain. The literature review was conducted to answer 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? To answer these questions, a review was conducted by searching for studies published in peer-reviewed indexed journals in an electronic database in the last 20 years. The identification of studies in scientific journals was performed following a three-step procedure, in light of the PRISMA standard guidelines, as shown in Figure 1.

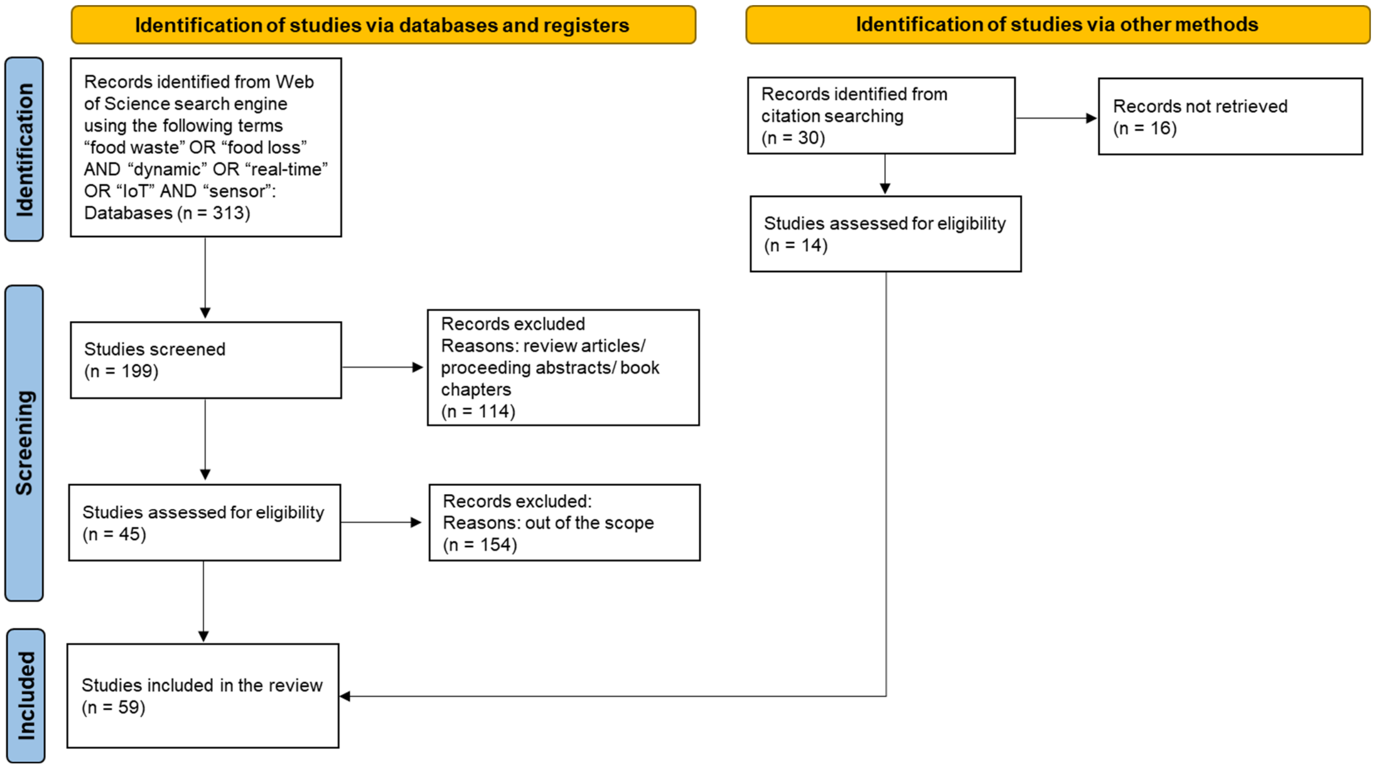

Figure 1. Studies identified and selected from the database.

Scientific articles were first systematically screened via the Web of Science search engine (https://www.webofscience.com/, accessed on 1 July 2022). 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. 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.

Several definitions of food loss and waste exist, and for this article, 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. After the third step, 45 articles met the inclusion criteria: real-time sensor assessing food waste in the food supply chain, original research articles written in English, and published online from 2001 to December 2021. During the review process, references of the studies were checked to identify additional studies of potential relevance, which led to the identification of 14 additional articles of interest. Cumulatively, this search resulted in the selection of 59 articles for the quantitative analysis. Three authors cross-checked the work to ensure no bias was introduced.

2.2. Data Synthesis

The selected relevant articles were analysed using a bibliometric networks method for co-occurrence analysis built using VOSviewer version 1.6.18, an open-access tool which aids in tracing the research development by producing informative maps of keywords and textual data. Co-occurrence networks can be synthesised based on data downloaded from the Web of Science and used to identify the relationships and interactions among different subject areas. Network visualisation offers a multidimensional scaling and clustering feature. It has been shown to be a powerful approach to analyse a large variety of bibliometric networks, such as the relations between keywords [23]. In network visualisation, the colour of a cluster indicates a particular property of the nodes. For instance, nodes may represent keywords, and the size of a node may indicate the number of times a keyword has been cited [24]. Terms that co-occur several times tend to be located close to each other in the visualisation.

2.3. IoT Architecture

The structure of the systematic literature review of sensing technologies in Section 3.3 was divided into four sections, following the components of the standard 4-layer IoT architecture. This architecture is described below.

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 devices (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 includes several layers, as described in Figure 2.

(1) 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.
(2) 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.
(3) Storage layer: includes data processing and storage, as well as dedicated functionality for each application and service, since emerging services have diverse requirements.
(4) 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.).

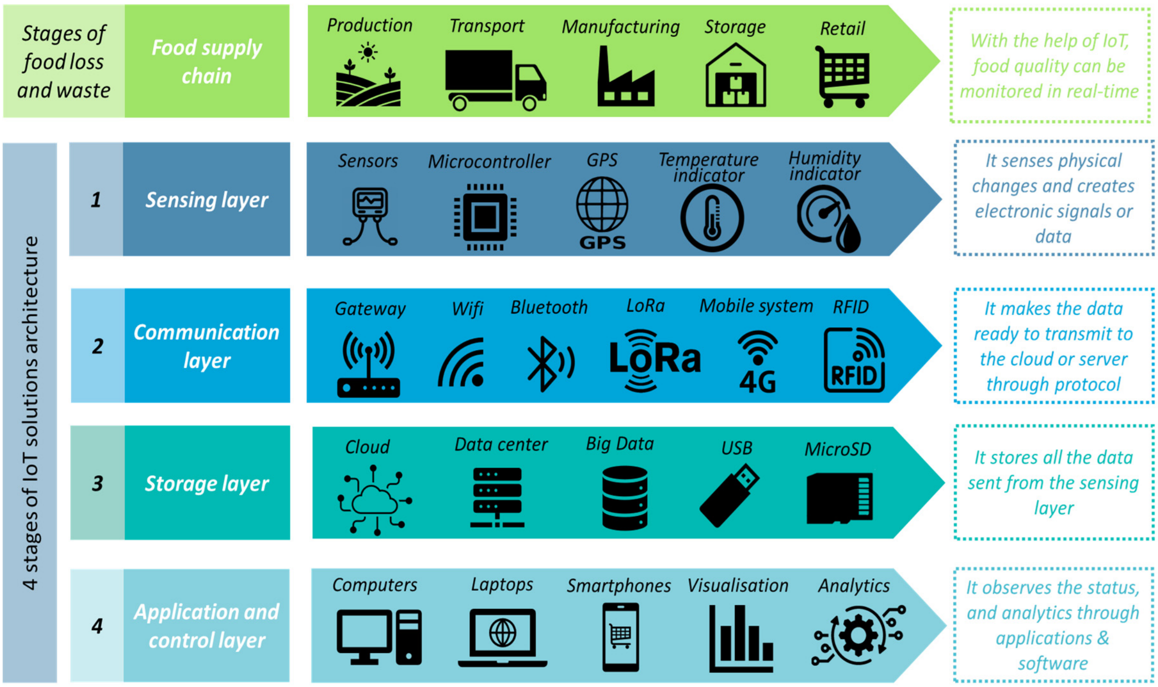

Figure 2. IoT architecture: (1) sensing layer, (2) communication layer, (3) storage layer, (4) application and control layer.

3. Results and Discussion

3.1. Analysis of Selected Papers

Food waste is recognised as a significant threat to food security, the economy, and the environment. In this regard, Figure 3 presents the efforts from the literature to overcome the challenges of reducing this type of waste using IoT technologies over the years. According to Figure 3, the oldest publication selected is from 2008, and the most recent is from 2021 (which is the latest year of this review). The increase observed during the years can be 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.

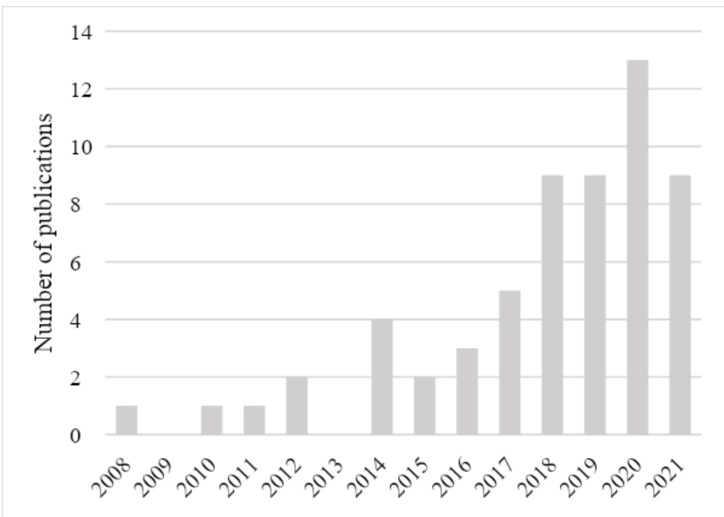

Figure 3. Number of publications per year.

Figure 4 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.

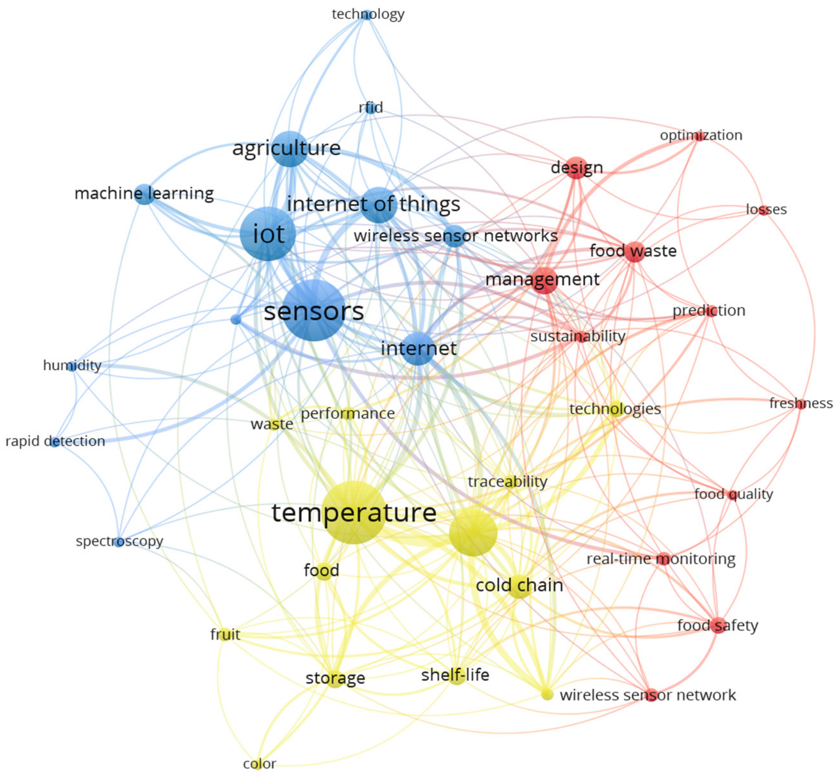

Figure 4. Network visualisation of the content.

3.2. Supply Chain Characteristics

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 elements related to the study application (food type, supply chain stage, and country) were extracted from each identified article and defined 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

Table 1. *Cont.*

Reference	Food Type	Supply Chain Stage	Country
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.

3.2.1. 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 5 presents the synthesis of the findings. The most commonly monitored application is Fruit, accounting for 32.1% of the total research. Further, by combining the Fruit and Vegetable categories from the analysis performed, this figure increases to almost half (48.15%) 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.

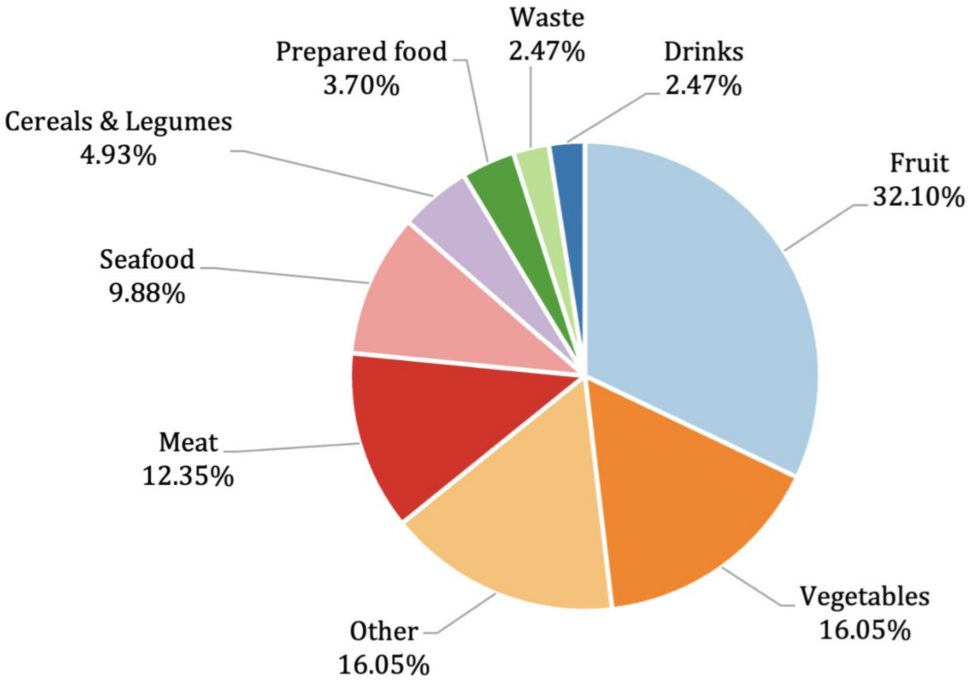

Figure 5. Business landscape by produce.

The analysis found the second most popular application to be that of Seafood and Meat, representing 22.23% 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.

The Other category also accounts for a significant proportion of food types monitored (16.05%), 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 70.38% 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 13.57% 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.

3.2.2. 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 6.

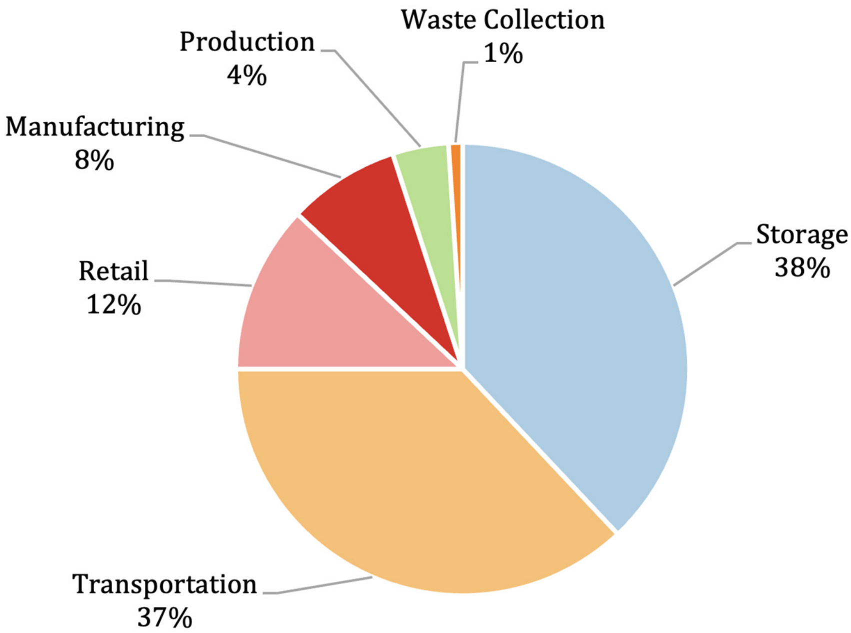

Figure 6. Business landscape by supply chain stage.

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 ambient 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 minimised.

3.2.3. 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. In the case of studies which did not include a real-world testing element, country was extracted based on the location of the corresponding author. The 59 studies were conducted over 22 different countries in total. Figure 7 presents a visualisation of the distribution of research papers by country.

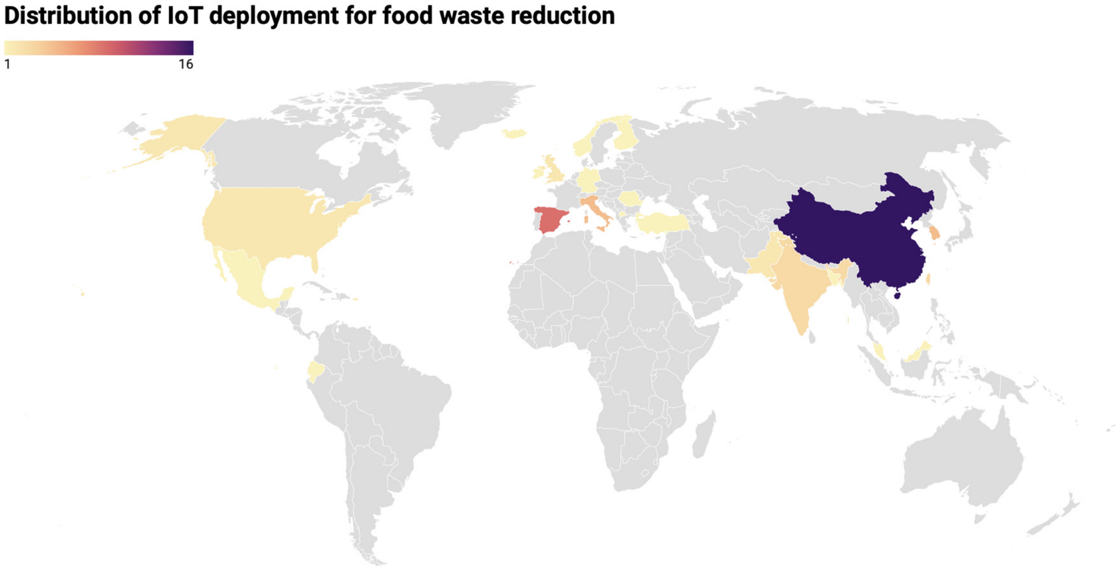

Figure 7. World maps of the distribution of research papers by country.

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.

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 USD17.7 trillion GDP, compared to India which has a GDP of USD2.6 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 (EUR 241 billion) in 2021 and is expected to reach 2 trillion yuan this year. In comparison, India's IoT market was valued at USD4.98 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 USD1.1 trillion, and the IoT revenue was valued at USD2.28 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).

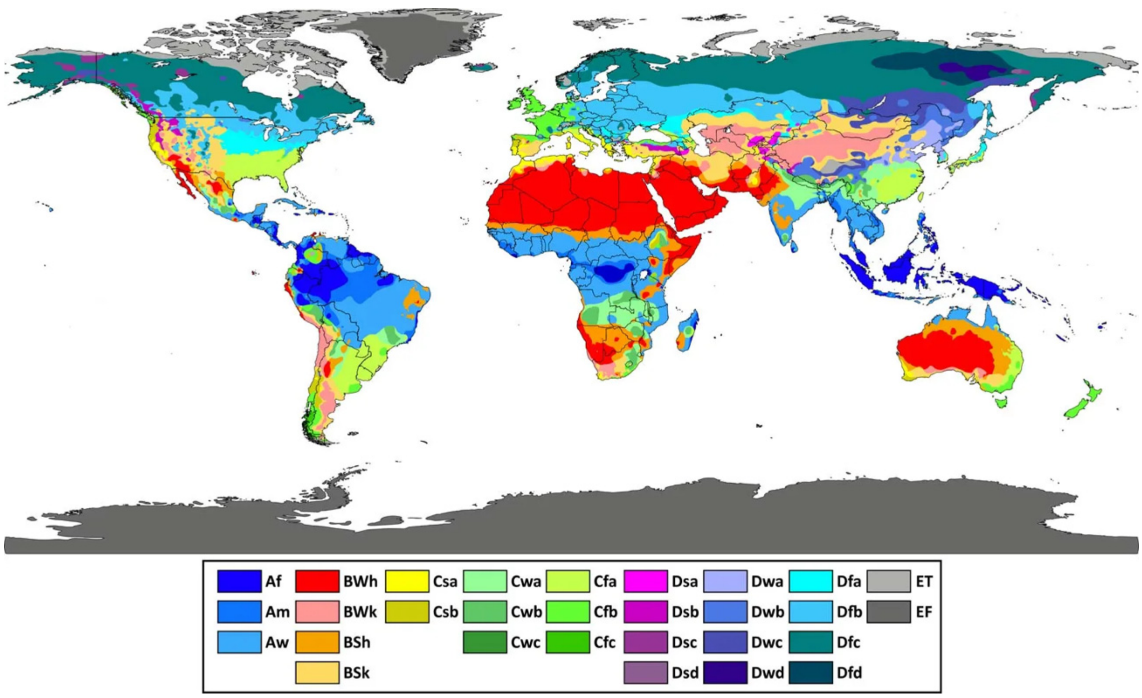

Figure 8. Köppen climate classification map [97].

Examining Figure 8, 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.

3.3. Real-Time Sensors in Food Supply Chains

This section will use the results from the systematic literature review to answer the last research question on "How have real-time monitoring technologies been employed in the food supply chain and its main aspects?".

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 recent 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.

3.3.1. Sensing Technologies—The Sensing Layer

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. 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.

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

Ref.	Sensing Technologies	Data Communication	Data Storage and Control	Applications and Software
[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 and 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

Table 2. *Cont.*

Ref.	Sensing Technologies	Data Communication	Data Storage and Control	Applications and Software
[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.

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 [104]. 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.

3.3.2. Sensing Parameters

Table 3 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 in Table 3, 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].

Table 3. Sensing parameters present in each article.

Reference	Temperature	Relative Humidity	Gas Composition	Location	Light Intensity	Pressure	Weight	Microbial Concentration	Vibration	Air Velocity	Other
[26]	X	X	X						X		
[27]	X	X	X		X						
[28]	X	X	X								
[29]	X	X	X			X					
[30]	X	X					X				
[31]								X			
[32]	X			X							
[33]			X								
[34]											X
[35]											X
[36]	X	X					X				
[37]	X	X									
[38]			X								
[39]	X	X	X								
[40]	X	X	X								

Table 3. *Cont.*

Reference	Temperature	Relative Humidity	Gas Composition	Location	Light Intensity	Pressure	Weight	Microbial Concentration	Vibration	Air Velocity	Other
[41]	X										
[42]	X	X									
[43]	X	X	X								
[44]	X										
[45]	X										
[46]	X	X									
[47]	X	X									
[48]	X	X									X
[49]											
[50]	X										
[51]	X	X	X								
[52]											X
[53]	X										
[54]											X
[55]	X	X									
[56]	X	X	X			X					
[57]	X	X			X						
[58]	X	X									
[59]				X			X				
[60]	X	X	X								
[61]	X	X	X								
[62]	X	X			X						
[63]	X										
[64]	X										
[65]	X	X									
[66]	X	X	X								
[67]	X	X	X								
[68]	X	X		X	X						
[69]	X	X		X							
[70]	X	X	X		X						
[71]								X			
[72]	X										
[73]	X										
[74]	X	X			X						
[75]	X	X			X						X
[76]	X										
[77]	X	X	X								
[78]	X	X	X								
[79]	X	X				X				X	X
[80]	X										
[81]	X					X				X	
[82]							X				
[83]	X	X		X					X		
[84]	X	X									

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.

3.3.3. 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.

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].

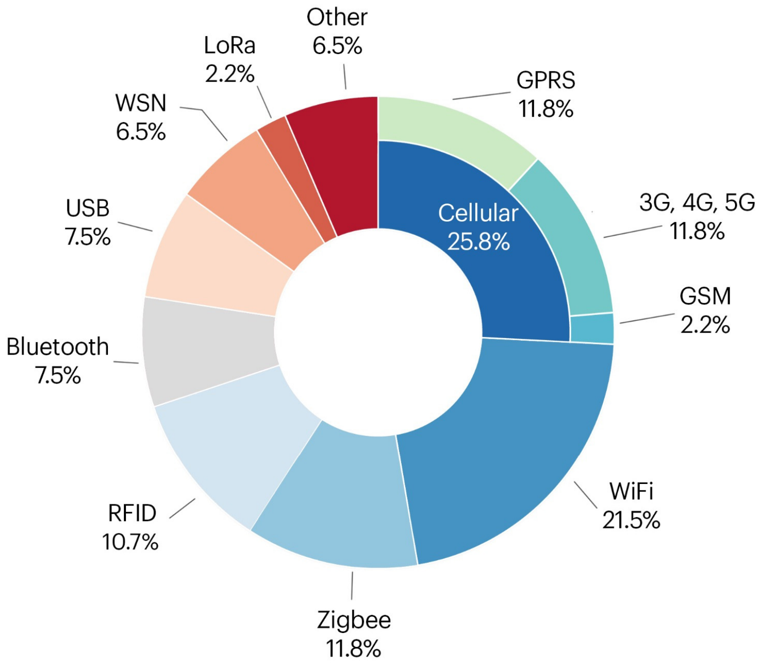

Figure 9. Communication options for IoT applications.

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 synchronisation 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 (10.7% 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 4 presents the characteristics of the main communication technologies available on the market in terms of frequency, data rate, range, energy consumption, etc.

Table 4. Communication technologies’ main characteristics. Adapted from Kazeem et al. [115] and Singh et al. [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 10 m), while Wi-Fi is oriented to WLAN (about 100 m). However, ZigBee can also reach 100 m 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 reliability, roaming capability, price and installation costs.

3.3.4. 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].

3.3.5. 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.

4. Conclusions and an Agenda for Future Studies

This study presented an overview of the current status of IoT applications 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 (32.1%), vegetables (16.05%), meat (12.35%) and seafood (9.88%). 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 (10.7%). 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.

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Abbreviations

3G, third-generation wireless; 4G, fourth-generation wireless; 5G, fifth-generation wireless; ADC, analog-to-digital converter; AI, artificial intelligence; API, application program interface; BIFTS, blockchain–IoT-based food traceability system; CMS, circuit monitoring systems; CNN, convolutional neural networks; CO2, carbon monoxide, DB, database; DHT, digital humidity and temperature sensor; DTU, data transmission unit; EEPROM, electrically erasable programmable read-only memory; EIS, electrical impendence spectroscopy; ENISA, European Union Agency for cybersecurity; EPCIS, electronic product code information services; ESP, Enhanced Service Provider; EU, European Union; FIFO, first in, first out; FLW, food loss and waste; FTIR, Fourier transform infrared; GDP, gross domestic product; GPRS, general packet radio service; GPS, global positioning system; GSM, global system for mobile; HACCP, hazard analysis and critical control points; HDD, hard disk drive; IBM, International Business Machines Corporation; ID3, iterative dichotomiser 3; IDE, integrated development environment; IEEE, Institute of Electrical and Electronics Engineers protocol; IoT, Internet of

Things; IoTRMS, Internet of Things-based risk monitoring system; IT, information technology; LAN, local area network; LCA, life cycle assessment; LCD, liquid-crystal display; LDR, light dependent resistors; LHT, light, humidity, temperature sensors; LIBS, Laser-induced breakdown spectroscopy; LoRaWAN, long range wide area networks; LTE, long-term evolution; MCU, micro-controller unit; ML, machine learning; MQTT, message queuing telemetry transport; MS, microsoft; NB-IoT, narrowband Internet of Things; NFC, near field communication; NIR, Near-infrared; NoSQL, not only structured query language; O2, oxygen; PC, personal computer; RFID, radio frequency identification; RH, relative humidity; RTC, real-time clock; RTD, resistance temperature detector; RTIMNS, real-time intelligent monitoring and notification system; SQL, Structured Query Language; SVM, support vector machine; UHF, ultra high frequency; USB, universal serial bus; VB, visual basic; VOC, volatile organic compounds; Wi-Fi, wireless fidelity; WSN, wireless sensor networks.

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Review

A Comprehensive Review on Food Waste Reduction Based on IoT and Big Data Technologies

Sahar Ahmadzadeh [1,*], Tahmina Ajmal [2], Ramakrishnan Ramanathan [3] and Yanqing Duan [1]

[1] Business and Management Research Institute (BMRI), University of Bedfordshire, Vicarage St., Luton LU1 3JU, UK
[2] Research Institute of Smart Cities (RISC), University of Bedfordshire, Park Square, Luton LU1 3JU, UK
[3] Essex Business School, University of Essex, Southend Campus, Elmer Approach, Southend-On-Sea, Essex SS1 1LW, UK
* Correspondence: sahar.ahmadzadeh@beds.ac.uk

Abstract: Food waste reduction, as a major application area of the Internet of Things (IoT) and big data technologies, has become one of the most pressing issues. In recent years, there has been an unprecedented increase in food waste, which has had a negative impact on economic growth in many countries. Food waste has also caused serious environmental problems. Agricultural production, post-harvest handling, and storage, as well as food processing, distribution, and consumption, can all lead to food wastage. This wastage is primarily caused by inefficiencies in the food supply chain and a lack of information at each stage of the food cycle. In order to minimize such effects, the Internet of Things, big data-based systems, and various management models are used to reduce food waste in food supply chains. This paper provides a comprehensive review of IoT and big data-based food waste management models, algorithms, and technologies with the aim of improving resource efficiency and highlights the key challenges and opportunities for future research.

Keywords: IoT sensors; food waste reduction; big data; communication technologies; supply chain

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1. Introduction

Food waste has been recognized as a serious issue, and significant efforts have been made worldwide to address the challenges and to reduce food waste. Simultaneously, there have been tremendous developments in the IoT sensor and big data technologies. These technological developments can transform the ordinary supply chains into smart supply chains, which can be adopted for reducing food waste using big data analysis approaches, appropriate models, and algorithms. There is broad literature for food waste control [1–9]. A smart supply chain uses information and communication technologies (ICT) to improve citizen welfare by providing better services through sharing information with the stakeholders. One of the most crucial aspects of a smart supply chain is the IoT infrastructure. Through various types of sensors, data can be sent to be analyzed to reduce food wastage. IoT applications are employed for a variety of purposes, for example, monitoring the environment inside homes [10] or in food processing factories [11].

The importance of Food Wastage Reduction (FWR) is related to the loss of all the natural resources in the supply chain, including expenditures related to the use of land, water supply, and energy consumption. Additionally, with respect to importance of sustainable agriculture, production, and supply chain, FWR will have major impacts on the economy, the environment, and society. It is critical to investigate how food wastage affects each of the three aspects. Yildirim et al. [12] discusses the economic impacts of FWR. To explain and better understand the determinants of food waste across the supply chain, Chalak et al. [13] closely examines the sectors of Hospitality, Restaurants, and Canteens/Cafeterias (HORECA), as well as the food retail and wholesale sectors. Data from 33 developed countries were analyzed by means of a regression model to identify the macroeconomic factors contributing to the generation of food waste. The challenges and opportunities for enhancing the emerging bioeconomy are explored in Morone et al. [14]. Additionally, Salemdeeb et al. [15] address the environmental aspects of using food waste. On the other hand, Scherhaufer et al. [16] explore the environmental effects of FWR which is an increasingly significant issue in smart cities. Sustainability is an extremely crucial issue that should be taken into consideration. The importance of sustainable food waste management is discussed by Mak et al. [17]. FWR models are widely discussed by Ananno et al. [18]. This literature supports the motivation for study on FWR based on IoT and big data technologies to control its negative environmental, social, and economic aspects.

Mak et al. [17] developed an IoT-based real-time FWR system for use in the office. They proposed a model in which an IoT-mounted weighbridge measures food wastage in office premises and reports it via a mobile device to the employees. Breakfast, lunch, dinner, and snacks are all considered as part of the measurement and can provide insight into how employees can reduce the amount of food lost at work. However, this proposed system does not discuss how various types of foods might be prevented from being wasted using this approach. Jayalakshmi et al. [19] implemented a novel approach for FWR through IoT-based smart garbage and waste collection bins. The embedded systems are used for measuring and recycling food waste to create social awareness and reduce food waste. In the present paper, a disposal system is presented that reduces the amount of food waste by reducing the total number of trips by garbage vehicles. In addition, it increases the overall cost associated with garbage collection. Gull et al. [20] used an Arduino Uno microcontroller to detect gas emissions from different food items, i.e., meat, rice, and bread. As explained in the paper, the MQ4 sensor detects the CH_4 gas, while the MQ135 sensor detects CO_2 and NH_3 in this system. A strain gauge load cell sensor and a converter as a weight sensor are used to measure the weight of the food being wasted. To ensure the accuracy and efficiency of the proposed system, the sensors are calibrated. Data is collected on cooked, uncooked, and rotten food items. A machine learning algorithm is used to predict food items based on gas emissions to make this a smart system. The decision tree algorithm is used for training and testing purposes. In this way, 70 instances of each food item are contained in the dataset. According to the rule set, this system is implemented to measure food wastage and to predict food items. When a specific food item is detected, data is gathered on how much of that food item is wasted in one day. This system had an accuracy of 92.65 percent. As a result, the system reduces the amount of food that is wasted at home and restaurants by providing a daily report of food wastage in their computer system. The application of IoT to FWR systems is also examined by Gayathri et al. and Luthra et al. [21,22], where [21] use RFID sensors as a key tool to monitor food waste for each individual in accordance with the proposed model, while [22] describe the application of IoT-based technologies to agricultural supply chain management in developing countries.

Thus, IoT and big data-based systems are finding more and more successful applications in FWR. However, based on an analysis of the literature, there is a paucity of a review that comprehensively analyzes the published literature, brings out the strong points of applications of IoT and Big Data technologies, and highlights neglected areas that might need more efforts from future researchers. This paper fills this void with a focus on food waste reduction. In this paper, we try to review different layers of IoT and big data infrastructure that merge together with the aim of reducing food wastage in the supply chain. This article provides a broad understanding of the patterns of prior studies in terms of the following aspects:

1. Reducing food waste with IoT and big data-based systems.
2. Machine learning algorithms that are used for FWR.
3. Various types of sensors and technologies that are used to reduce the amount of food wastage and improve food quality.
4. The challenges and opportunities related to using IoT and big data analysis for reducing food wastage in the supply chain.

This paper is structured as follows: Section 1 is an introduction and discusses the motivation and describes the relevant literature. Section 2 discusses research in IoT and big data analytics for FWR. The next sections explain the three layers of the FWR system. In Section 3, FWR based on IoT and Big Data analytics in Smart Supply Chain for the sensing and measurement layer is discussed. In Section 4, the service layer and big data analysis approaches for FWR are discussed, and a review of articles for understanding the models and algorithms is presented. Section 5 provides an investigation into the application of Machine Learning Techniques in reducing food loss. Section 6 introduces wireless technologies to reduce food waste. Section 7 provides a review of the challenges and opportunities related to an IoT-based FWR system. Finally, Section 8 concludes the paper. A list of acronyms used throughout the paper is presented in Table 1.

Table 1. List of acronyms and corresponding definitions.

Acronyms	Definitions
IoT	Internet of Things
FWR	Food Waste Reduction
MEMS	Microelectromechanical Systems
RF	Radio Frequency
BLE	Bluetooth Low Energy
WLAN	Wireless Local Area Network
ANN	Artificial Neural Network
SVM	Support Vector Machine
RFID	Radio Frequency Identification
GMM	Gaussian Mixture Model
KNN	K-Nearest Neighbourhood
WSN	Wireless Sensor Network
ML	Machine Learning
AI	Artificial Intelligence

2. IoT and Big Data

IoT technology through ICT infrastructure and smart devices combines to gather huge amounts of data in real-time, which is commonly known as big data. The big data generated by IoT devices will be stored in the big data storage system and will be used for analysis. The relationship between big data analytics and IoT is explained by Marjani et al. [23] by taking into account the architecture, opportunities, and open research challenges. Furthermore, this paper also covers big IoT data analytic types, methods, and technologies for big data mining. Additionally, the IoT architecture in relation to big data analytics is studied. IoT devices are connected to the network and the data is then stored in the cloud and then analyzed. In our paper, we enhanced the topic to IoT applications in smart food supply chains. In this section, IoT and big data are briefly discussed, and the relationship between IoT and big data analytics is explained in more detail.

2.1. IoT

According to Marjani et al. [23] and Al Nuaimiet al. [24], IoT offers a platform for sensors and devices to communicate seamlessly within a smart environment and enables information sharing across platforms in a convenient manner. Smart cities have seen a recent adoption of IoT. This is due to interest in intelligent systems, such as smart offices, smart retail, smart agriculture, smart water, smart transportation, smart healthcare, and smart energy. By using different types of sensors based on their application and communication technology, IoT is used in smart supply chains to reduce food wastage.

Figure 1, inspired by Jagtap et al. [25], illustrates IoT as a platform for FWR in a smart supply chain. As is illustrated, the four layers of sensing, application, network, and service form an IoT system, which is indicated for FWR applications.

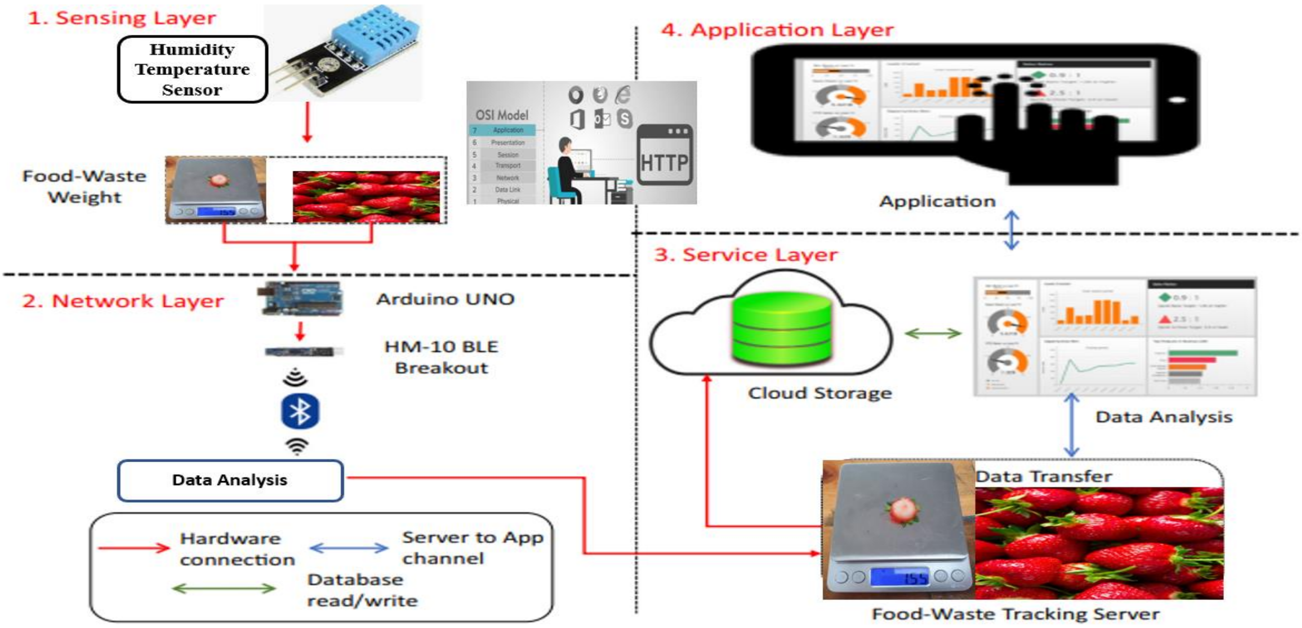

Figure 1. IoT platform for FWR [23].

2.2. Big Data

The massive data generation by sensors, devices, social media, healthcare applications, temperature sensors, and various other software applications and digital devices that continuously generate large amounts of structured, unstructured, or semi-structured data results in big data. Mak et al. [17] describe big data technologies as an upcoming generation of technologies and architectures. These technologies aim to take the value out of a massive volume of data in a variety of formats. This is done by enabling high-velocity capture, discovery, and analysis. In the studies conducted by Kambatla et al. [26] and Gantz et al. [27], trends and approaches for big data analysis are discussed. There are various characteristics of big data, such as veracity, value, variability, and complexity. These characteristics include the volume or size of data, variety or different sources of data, and velocity or speed of data creation, which are studied by Gani et al. [28] and Paul et al. [29]. Big data analytics is the process of examining large data sets that contain a variety of data types to reveal unseen patterns.

Data analytics consists of estimating hidden correlations, customer preferences, and other useful business information [30]. Having a clear understanding of data is the most significant objective of big data analytics, which helps food production companies to make efficient decisions. Big data analytics require technologies and tools that can transform a large amount of data into a more understandable data format for analytical processes. There are algorithms and tools that are used for the purpose of data analysis. Tools like these are used to identify patterns in data over time and visualize them as tables and graphs. Therefore, the performance of current algorithms for data analysis is a challenging issue that should be taken into consideration [31]. There are various tools and platforms that are in use for the purpose of data analysis; however, the most critical approach is to process huge data sets within a reasonable amount of processing time [32,33]. The data can be collected through various sources including online food quality databases, smartphones and handheld devices, social media, and satellite imagery. There are different types of data analytics, which are explained as follows:

- Real-time analytics (RTA)

Real-time analysis is typically performed on data gathered from sensors. Clearly, data changes constantly in this scenario, so rapid data analytics techniques are required to get an analytical result. It consists of two architectures: parallel processing clusters and memory-based computing platforms, which are detailed by Pfaffl et al. [34] The applications and challenges of big data analysis are discussed in [35]. A description of RTA architecture in the sustainable industry 4, the fourth stage of an industrial revolution, is provided by Novak et al. [36].

- Off-line analytics (OLA)

Off-line analysis is used when a quick response is not required [37]. For example, many Internet enterprises use Hadoop-driven offline analytics as explained in Zahid et al. [38]. There are other approaches for big data analytics such as memory-level analytics, business intelligence analysis, and massive analysis, which are defined based on the size of data in comparison with the allocated memory based on the application, which is explained in Refs. [39,40], respectively. The relationship between IoT and big data analytics is explained in Figure 2.

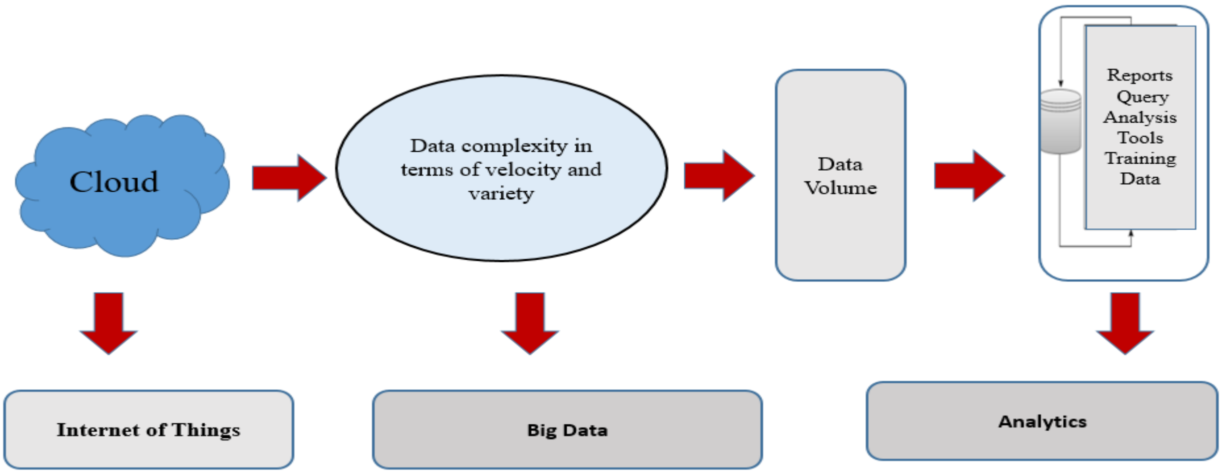

Figure 2. Relationship between IoT and big data analysis [23].

Nguyen et al. [41] present a state-of-the-art literature review on big data analysis for supply chain management. Arora et al. [42] provide an overview of big data analysis methods and procedures. Additionally, a comparison between various big data analysis techniques is provided as well. This is further explained in the following sections with more focus on FWR in the supply chain.

3. FWR Based on IOT and Big Data Analytics in Smart Supply-Chains: Sensing and Measurement Layer

In the work by Anagnostopoulos et al. [43], a visual tree for waste management is developed. It can be further developed to reduce food waste. Figure 3 illustrates how to classify the technologies that reduce food wastage. Anagnostopoulos et al. [43] review the literature related IoT-based technologies for reducing food waste in different layers of sensing and measurement, processing, and data transmission. As illustrated in Figure 3, there are various technologies that are used for the purpose of minimizing food waste. In the following sections, we examine these technologies and discuss the challenges. The term ‘smart’ refers to the process of checking the quality of food based on sensing and data analysis approaches, which will be discussed in more detail later. Here, we review the sensor technologies and introduce various types of sensors and their applications to better understand the measurement and data collection process in advanced IoT-based systems that aim to minimize food waste. Sehrawat et al. [44] review various types of IoT sensors. Table 2 provides a definition of these sensors and their applications in the food supply chain.

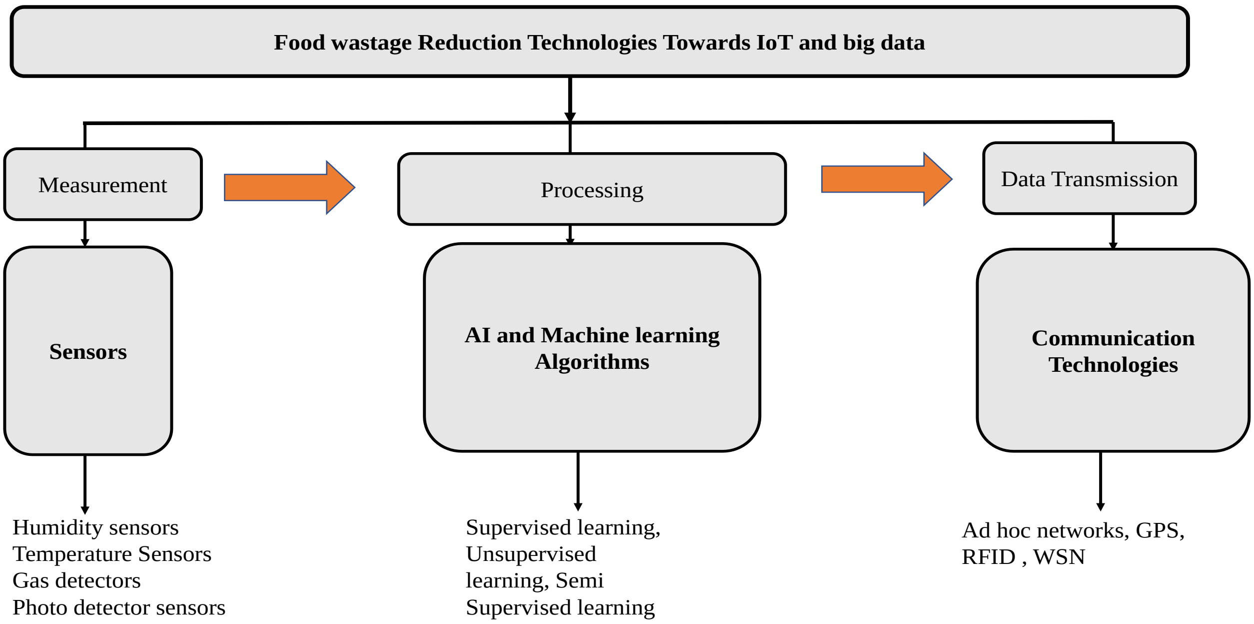

Figure 3. Ingredients of smart food waste reduction technology based on IoT and Big data analysis.

Table 2. Categorisation of the sensors for FWR and the applied technology.

Sensor Type	Technology	Application	Reference	Year
Proximity Sensor	The position of any nearby object is detected without any physical contact by emitting electromagnetic radiation such as infrared and looking for any variation in the return signal	Multi-application, depending on the type. There are various types such as inductive, capacitive, ultrasonic, photoelectric, and magnetic. Mostly used in applications demanding security and efficiency. Main applications of FWR are cutting number of items, measuring the amount of rotation for positioning of objects, and measuring movement direction.	[20,44,45]	2019, 2020, 2021
Position and occupancy sensors	Detection of the presence of human or objects in a particular area by sensing the air, temperature, humidity, light, and motion of a nearby object	Security and safety purposes, smart agriculture, smart FWR	[46,47]	2017
Motion and Velocity sensors	Motion sensors detect all kinds of physical movements in the environment and the velocity sensors calculates the rate of change in position measurement at known intervals in linear or angular manner	Smart city applications for intelligent vehicle monitoring, for example, acceleration detection of the boxes of food in the trucks for food protection during transmission	[48,49]	2015, 2016
Temperature sensors	Measurement of heat energy	FWR and smart farm	[50,51]	2016, 2018
Pressure sensor	Measurement the amount of force and convert it to signal	Smart FWR, smart refrigerator	[52]	2018

Table 2. *Cont.*

Sensor Type	Technology	Application	Reference	Year
Chemical sensors	Conversion of a chemical or physical property of a specific analyte into a measurable signal that its magnitude is normally proportional to the concertation of the analyte.	FWR and smart agriculture	[53]	2020
Optical sensors	Light intensity measurement	Food industry, FWR For instance, assessment of wine grape phenolic maturity based on berry fluorescence	[54,55]	2021, 2008

- Proximity Sensors: The proximity sensors are intended to detect a nearby object using electromagnetic radiation such as infrared by detecting variations in the return signal. There are various types of these sensors, such as inductive, capacitive, ultrasonic, photoelectric, and magnetic [44]. These sensors are widely used in the food industry and in FWR systems [20].
- Position Sensors: The position sensor senses the motion of an object in a certain area to detect its presence. It can be used in smart agriculture and in IoT-based FWR systems [46]. There are also motion sensors that can be considered in this category that are designed to sense all kinds of kinetic movements of an object, as described by Ref. [56]. Ndraha et al. [57] apply various types of sensors including position sensors for the improvement of cold chain performance and improper handling.
- Occupancy Sensors: These sensors are used for the remote monitoring of variables such as temperature, humidity, light, and air [47].
- Motion or Kinetic Sensors: The sensor detects all kinetic and physical movement in the environment [56] and could be used in a truck to detect possible movement of fruit boxes to provide needed information to estimate the rate of food deterioration in a certain period for better decision-making.
- Velocity Sensors: The velocity sensors calculate the rate of position variation, which might be linear along a straight line or angular related to device rotation speed at known intervals [48]. These sensors can be used in crates to determine the variation of food position during food transfer. This will enable us to monitor the parameters that can affect food quality and make the appropriate decisions.
- Temperature sensors: Temperature sensors are widely used for the monitoring of environmental conditions of the surroundings [50]. This type of sensor is also widely used in FWR systems and more, especially for smart agriculture to enable farmers to increase their overall yield and product quality by getting real-time data on their land [51].
- Pressure Sensors: Pressure sensors sense the amount of force and convert it into signals. Sensors of this type can be used to measure the amount of pressure in boxes of food and send the data to the server for decision-making to avoid food waste caused by excessive pressure in boxes during transport. The sensor triggers a notification to the user as soon as the applied pressure is below a certain value that affects the quality of the food [52,58].
- Chemical Sensors: These types of sensors sense any chemical reaction and can be used for reducing food wastage in smart agriculture [53].
- Optical Sensors: Optical sensors are a broad class of devices for detecting light intensity. Optical sensors are suitable for IoT applications related to the environment. Therefore, they can be used for food quality control applications, in the food industry [55], and in smart agriculture [54].

4. Processing the Aggregated Data: Service Layer

There is a broad range of literature on the application of Machine Learning (ML) for IoT big data analytics [59,60]. Data from the sensors need to be processed; this section reviews the algorithms that are mostly used in IoT-based food quality monitoring systems.

4.1. ML and Predictive Models

ML methodologies consist of a learning process with the objective of learning or experiencing trained data with the aim of performing a task. The data in ML might be nominal, binary, or numeric. The performance of the ML models is measured by a metric using various statistical and mathematical models. The trained model can be used to predict or cluster new examples. Figure 4 illustrates the ML approach.

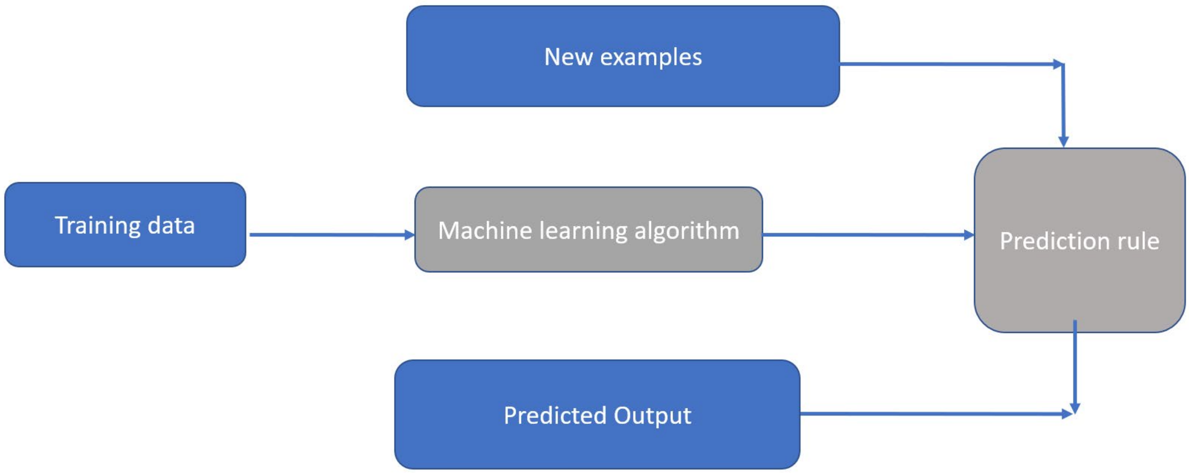

Figure 4. Illustration of ML approach.

In ML algorithms, the learning process might be divided into supervised or unsupervised based on various types of learning models such as classification, regression, clustering, and dimensionality reduction. In the supervised setting, the trained model is applied to predict the missing outputs and labels for the test data. On the other hand, in unsupervised learning, there is no distinction between training and test sets, and the data is unlabeled. The input data is trained with the goal of discovering hidden patterns. Our objective in this section is to review ML-based predictive models that are mostly used for data analysis approaches in agriculture 4, which focuses on precision agriculture based on IoT technologies and big data analysis. Liakos et al. [61] explore various machine learning algorithms for agricultural production.

In predictive models, solving the problem of finding a function that maps a vector of specific length to an output variable to estimate some unknown model parameters is called a regression problem. There are various types of regression models that are used for solving regression problems, such as linear regression models, tree-based models including regression trees, bootstrap aggregated trees, random forests, gradient boosting, and regularization techniques [62]. Data dimensionality reduction (DR) is applied in both supervised and unsupervised learning types, with the aim of providing a lower-dimensional representation of data to simplify computation. Principal component analysis, partial least squares regression, and linear discriminant analysis are some of the most common DR algorithms, as discussed in Refs. [63–65]. All these techniques are widely used for analyzing data in agriculture 4 for decision-making applications.

4.2. Learning Models

The presentation of the learning models in ML is limited to the works presented in this review.

(1) Regression: The regression approach is based on supervised learning with the objective of providing the prediction of an output variable according to the input known variables. There are various types of regression problems that are studied in the literature, such as linear and logistic regression [66,67], stepwise regression [68], ordinary least squares regression [69], multivariate adaptive regression spline [70], multiple linear regression [71], cubist [72], and locally estimated scatter plot smoothing [73].
(2) Clustering: Clustering is widely used as an unsupervised learning approach for group clustering of data. Some examples of this approach include K-means [74], a hierarchical technique [75], and an expectation maximization technique [76].
(3) Bayesian Models: The type of Bayesian model belongs to the supervised learning category, and it can be used for solving regression or classification problems. The Bayesian model is a kind of probabilistic graphical model. There are various types of this algorithm, including Naive Bayes [77], Gaussian Naive Bayes [78], multinomial Naive Bayes [79], Bayesian network [80], and Bayesian belief network [81].
(4) Instance-Based Models: Instance-driven models (IBM) are memory-based models that learn by comparing new examples with instances in the training database. This algorithm generates predictions based on specific instances. This type of algorithm faces a disadvantage because the complexity grows with the data. Examples of these learning algorithms are k-nearest neighbor [82], locally weighted learning [83], and learning vector quantization [84].
(5) Decision Trees: According to the definition provided in [85], decision trees are classification or regression models formulated in a tree-like architecture. With these tree-based algorithms, the dataset is progressively organized into smaller homogeneous subsets or sub-populations. In tree-based algorithms, the leaf nodes represent the final decision or prediction taken after following the path from the root to the leaf which is expressed as a classification rule. The most common learning algorithms in this category consist of the classification and regression trees [86] and the chi-square automatic interaction detector [87].
(6) Artificial Neural Networks: ANNs are inspired by human brain functionality. It is mostly used for solving problems in pattern recognition, cognition, and decision-making. In ANN several nodes are arranged in multilayers consisting of an input layer that feeds the data into the system, some hidden layers for doing the process of learning, and an output layer where the decision is given. ANNs have basically supervised models that are used for solving regression and classification problems. Deep ANN is a new area of ML research that applies multiple levels of abstraction to solve computational models that are composed of multiple processing layers. DNNs are simply ANN with multiple hidden layers between the input and output layers and can be either supervised, partially supervised or even unsupervised. A convolutional neural network (CNN) is a common DL model where the feature maps' extraction is performed by convolutions in the image domain. There is a wide range of algorithms that are commonly used for ANN and DNN. Table 3 provides a review of these algorithms.
(7) Support Vector Machines: SVM is basically a binary classifier that is used for data classification. A kernel trick can be implemented to upgrade traditional SVMs through the transformation of the original feature space into a feature space of a higher dimension. This algorithm is widely used in IoT-based food reduction algorithms. Table 4 reviews the functionality of this algorithm alongside other ML algorithms for reducing food wastage using advanced IoT technologies.

Table 3. Categorization of artificial neural network algorithms.

ANN Algorithm	Deep ANN Algorithm	Paper	Year
Radial basis function networks	——-	[88]	1996
Convolutional Neural Network	✓	[89]	2017

Table 3. *Cont.*

ANN Algorithm	Deep ANN Algorithm	Paper	Year
Perception Algorithms	——	[90]	2002
Back Propagation Algorithms	——	[91,92]	1998, 2021
Resilient Back Propagation Algorithm	——	[93,94]	1996, 2021
Deep Boltzmann Machine	✓	[95]	2019
Counter Propagation Algorithms	——	[96]	2008
Adaptive Neuro Fuzzy Inference Systems	——	[97]	2020
Generalized Regression Neural Network Algorithms	——	[98]	2010
Deep Belief Network	✓	[99]	2015
Hopfield Networks	——	[100]	2020
Multilayer perception Algorithms	——	[101]	2005
Auto-encoders	✓	[102]	2020
Extreme Learning Machines	——	[103]	2011

5. Application of Machine Learning Algorithms for FWR: Application Layer

IoT-based food waste reduction has benefited from technological advancements, particularly by incorporating industrial advances into a sustainable agriculture production system. Each year millions of tons of food are wasted around the globe. This negatively affects the economy of the country. Machine learning's adaptability, promotion, and reduced costs help in assessing the complicated link between the input and output of agricultural systems by utilizing analytical approaches [104]. Applications of machine learning and artificial intelligence in reducing food wastage have been studied in the literature, which is represented in Table 4.

Table 4. Application of ML and AI algorithms for FWR based on IoT technologies.

ML Algorithm	Functionality	Paper	Year
SVM	Automatic count of coffee fruits on a coffee branch	[105]	2017
ANN	Method for the accurate analysis for agricultural yield predictions	[106]	2016
Regression, SVM	Estimation of monthly mean reference evapotranspiration arid and semi-arid- regions	[107]	2017
Bayesian Models	Detection of Cherry branches with full foliage	[108]	2016
Deep Learning	Identification and classification of three legume species: soybean, and white and red bean	[109]	2016
ANN	Estimation of daily evapotranspiration for two scenarios	[110]	2017

As is explained in Table 4, Machine Learning algorithms such as SVM, ANN, Regression, and Bayesian models are used for FWR in different stages of production to enhance the quality of food products. In Ramos et al. [105] SVM is used to classify the ripe, overripe, and unripe coffee fruits. In Kung et al. [106] ANN is used for agricultural yield prediction. Mehdizadeh et al. [107] and Amatya et al. [108] use multivariate adaptive regression and Bayesian models for the estimation of the monthly mean and detection of cherry branches respectively. In order to provide high-quality food for consumers after prediction, appropriate communication is needed for the transportation of the information after sensing the temperature or other vital parameters such as environmental humidity that can significantly have an impact on the quality of the produced food for proper decision-making purposes to transfer the food to the closet customer.

With respect to the importance of communication technologies for FWR, communication technologies in the food supply chain are explained in the next section.

6. Wireless Communication Technologies for FWR in Smart Supply Chains: Network Layer

In this section, an overview of the various wireless communication technologies is presented. Different technologies are compared in terms of data transmission range and power consumption. By following this section an understanding of various wireless communication technologies will be provided to be considered based on the application requirements and the trade-off between transmission range and battery consumption. There are a variety of wireless communication technologies, such as RFID, GPS, narrowband (NB-IoT), long-range (LoRa), and ZigBee, which can be used for IoT applications to transfer measurements to reduce food waste. A comparison between different wireless communication technologies with energy harvesting capabilities for FWR is provided by Sadowski et al. [111]. Table 5 provides a comparison between wireless communication technologies based on data rate, cost, and transmission range. A categorization of wireless communication technologies and their application in FWR is explained as follows:

Table 5. A comparison between different Wireless communication technologies [111].

Wireless Communication Technology	Data Rate	Range	Cost
Wi-Fi	100 MBps	10–40 m	Moderate
Bluetooth	1 MBps	10–30 m	Low
Bluetooth Low energy, and Zigbee	100 KBps	100 m	Low
RFID	1 KBps	1–9 m	Very Low
Cellular 5G/LTE/3G	1 MBps–100 MBps	1–10 km	High
LPWAN	150 KBps	1–20 km	Moderate-Low

(1) Low Power Wide Area Networks: LPWANs are widely used in IoT applications. For large-scale IoT networks, small, inexpensive batteries that last for years are used for long-range communication. The main application of these technologies is in the industry and commercial sectors. As LPWANs can connect all types of IoT sensors, they can be used for IoT applications in the food industry. With this technology, countless applications can be achieved, such as asset tracking, environmental monitoring, and facility management. Regarding the characteristics of LPWANs, only small blocks of data can be transferred at a low rate. Therefore, this technology is better suited for low bandwidth and not time-sensitive applications. It should be noted that selecting the most appropriate wireless technology for IoT use cases specified in the food supply chain requires an accurate assessment of bandwidth, QoS, security, power consumption, and network management. Here, in the rest of this section, other types of wireless technologies that can be applied in the food supply chain are explained.

(2) Cellular (3G/4G/5G): Different generations of mobile communication technologies and cellular networks offer reliable broadband communication that supports various voice calls and video streaming applications that are good for monitoring food quality, however, these technologies impose very high operational costs and power requirements that should be considered for their applications. Although cellular networks are not viable for the majority of IoT applications powered by battery-operated sensor networks, they fit well in specific use cases such as connected cars or for management applications in transportation and logistics. In the case of tracking trucks carrying food, the technology can be applied by relying on cellular connectivity, which is ubiquitous and high-speed. IoT applications in the food supply chain can be used with the next-generation 5G network with its high-speed mobility and low latency.

It can support real-time video surveillance for food quality control, real-time mobile delivery of measured parameters such as humidity and temperature, as well as relevant datasets for connecting several time-sensitive automation applications in the food supply chain that focus on food quality.

(3) Zigbee and Other Mesh Protocols: Zigbee is a short-range, low-power, wireless standard that is also referred to as IEEE 802.15.4. This wireless communication technology is commonly deployed in a mesh topology to extend coverage by relaying sensor data over multiple sensor nodes and therefore it is very useful for IoT-based technologies in the food supply chain. Compared to LPWAN, Zigbee provides higher data rates and much less power efficiency due to mesh configuration. As this technology is most suited for medium-range IoT applications with an even distribution of nodes in close proximity, it is suitable for monitoring the humidity and temperature in fridges and freezers to send an alarm in critical situations. Zigbee is a perfect complement to Wi-Fi for various IoT applications to monitor food quality and transfer measured data for further processing. This technology provides several remote monitoring solutions for applications for reducing food wastage.

(4) Bluetooth and Bluetooth Low Energy (BLE): Bluetooth technologies are defined in the category of Wireless Personal Area Networks (WPANS) a short-range communication technology that is originally intended for point-to-point or point-to-multipoint (up to seven slave nodes) data exchange devices. BLE devices are typically used in smartphones that serve as a hub for transferring data to the cloud. In today’s world, BLE is widely used to transfer data from humidity, temperature, and acceleration sensors directly to the smartphone app to be analyzed and visualized. The BLE devices are widely used in retail contexts to provide versatile indoor localization features for in-store navigation and content delivery.

(5) Wi-Fi: Wi-Fi has a critical role in providing high throughput data transfer, however, in the IoT space, its major limitations in coverage, scalability, and high-power consumption make this technology less prevalent. Therefore, it is often not a feasible solution for large networks of battery-operated IoT sensors, especially in industrial IoT applications. As the coverage is almost good in comparison with other wireless technologies, Wi-Fi can be applied in IoT applications for food quality control purposes.

(6) RFID: It uses radio waves to transmit small amounts of data from an RFID tag to a reader within a very short distance. This technology is widely used for indoor data transfer in food quality monitoring applications. Additionally, RFID has facilitated a revolution in retail applications and logistics. To optimize supply chain management, RFID tags can be attached to food bags to track parameters such as acceleration, humidity, and temperature. Some of the applications of RFID in the retail sector consist of smart shelves, smart fridges, smart bags, and so on.

7. IoT-Based Food Wastage Reduction Challenges and Opportunities

7.1. Challenges

Although data analysis tools are used to monitor food quality features, there are several challenges that should be taken into consideration. In Ali et al.’s work [3], various risks in the food industry are analyzed. Additionally, Jin et al. [112] provide a review of big data in food quality monitoring. Some of the challenges in food safety are studied by Wang et al. [113]. Based on the literature review conducted in this study, a number of key challenges are identified and listed below:

- Data Quality: Research on Big Data Analytics in food quality control using cloud computing technology has its own relevant challenges related to data quality, scalability, availability, and integrity.
- Lack of Standardization: These can be related to using different management systems by users and can be considered the biggest challenges related to the generated data.
- Lack of Communication Protocols: Bouzembrak et al. [114] explain that this can be considered one of the main issues that affect the data transmission quality, as it may

cause delays, or some parts of the measured data might be missed due to a lack of reliable communication protocols.

- Security and Data Protection: Several issues are associated with IoT security in food quality control, such as inadequate hardware and software security. Additionally, IoT nodes that are not supported with enough security protocols can be a vulnerable point for the security of the entire IoT system along the food supply chain.
- Battery: The energy consumption issues related to the use of batteries also pose significant challenges to the success of IoT-based technologies for FWR.

According to Amer et al. [115], the challenges of using IoT in the food supply chain can be divided into technical, financial, social, operational, educational, and governmental.

The technical challenges contain hardware-related technical skills. It can also refer to network structure, and big data management and analytics capabilities. The financial challenges mostly refer to operation and management costs. There are also social challenges related to cooperation among supply chain players as well as integration and coordination of information among supply chain partners. The operational challenges are mostly in line with administrating supply chain IoT networks, data security, and industry operating IoT standards.

In addition, mobile-based applications can, in some cases, negatively contribute to the food waste phenomena [116–118].

7.2. Opportunities

IoT technologies will give companies many opportunities to reduce food waste. In this context, we cite the ongoing REAMIT project (https://www.reamit.eu/, accessed on 1 December 2022), which was founded by Interreg Northwest Europe. REAMIT provides several IoT-based food monitoring and control opportunities with the aim of FWR in food companies that are summarized as follows:

- Networking and Collaborations: These provided access to a network in North-West Europe with wide expertise and provided an opportunity for participation in future collaboration initiatives.
- Quality Assurance: Continuously monitor food quality and signal any potential loss in quality.
- Decision support and decision-making: Using big data analytics and artificial intelligence to provide rapid decision support for food logistics.
- Sensor Technology: Providing at the forefront of sensor (traditional and advanced) technologies for monitoring food quality and big data technology developments
- Data-Driven Decision-Making: Making the right decision for food quality based on carefully analyzing real-time data.

With the development of IoT monitoring systems, two main advantages will be achieved. In the first place, notifications can provide fresh information for the companies and suppliers to prevent food wastage, and in the second place, there are environmental benefits such as reducing carbon footprints that arise from IoT and big data analysis being combined with the overall aim of reducing food wastage in smart supply chains with IoT based infrastructure that can run FWR programs. In line with motivations and challenges for food companies in using IoT sensors for the purpose of FWR, Ramanathan et al. [119] provide insight and a roadmap for the future.

Figure 5 visualizes REAMIT approaches:

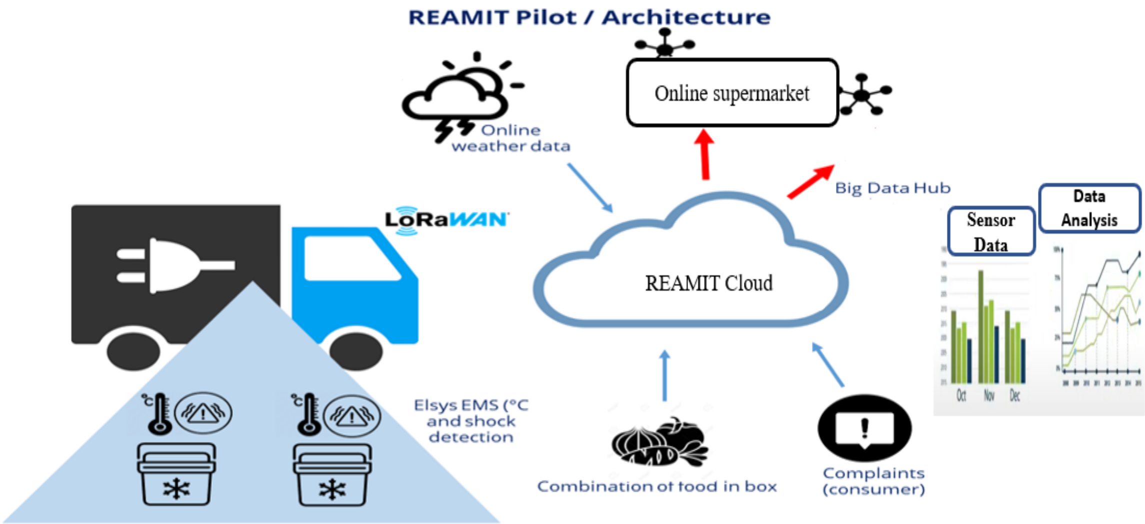

Figure 5. REAMIT approaches visualization.

8. Conclusions

The main objective of this review paper is to combine the most pertinent aspects of IoT with the main goal of reducing food wastage in food supply chains. This paper has provided a comprehensive review of the use of various IoT and Big Data technologies. It discusses how to reduce food waste from farm to fork along the food supply chains by integrating different technologies to create an IoT system. This paper reviews sensors, ML algorithms, and wireless data transmission technologies, which are the key components of IoT systems. It focuses on their applications for monitoring food quality and reducing wastage. The findings contribute to understanding how the IoT sensors and big data technologies can be used to reduce food waste. The paper also raises awareness of the challenges and opportunities faced by researchers and practitioners when implementing IoT-based systems for food waste reduction. Based on the review, this paper has identified a list of the most researched and least researched areas in terms of the application of IoT and big data technologies for reducing food waste. It finds that FWR is widely reviewed in terms of big data analysis; however, further investigation on the methods, approaches, and sensor types that can be applied to specific kinds of food is needed. For instance, for vegetables, what kind of sensor is optimal to use to reduce their wastage? What types of sensor data (e.g., odor, color, temperature) are most effective to indicate the freshness of vegetables? This research can be further expanded to other food categories such as meat, cooked foods, frozen foods, fish, fruits, etc. This study is intended for future research in this area.

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Article

Adapting Digital Technologies to Reduce Food Waste and Improve Operational Efficiency of a Frozen Food Company—The Case of Yumchop Foods in the UK

Usha Ramanathan [1,*], Ramakrishnan Ramanathan [2], Abiodun Adefisan [3], Tamíris Da Costa [4], Xavier Cama-Moncunill [4] and Gautam Samriya [5]

1 Nottingham Business School, Nottingham Trent University, Trent NG1 4FQ, UK
2 Essex Business School, University of Essex, Essex SS1 1LW, UK
3 Yumchop Foods, Towcester NN12 6HX, UK
4 School of Biosystems & Food Engineering, University College Dublin, Agriculture Building, UCD Belfield, D04 V1W8 Dublin, Ireland
5 MTU Kerry Campus, Munster Technological University, V92 HD4V Tralee, Ireland
* Correspondence: usha.ramanathan@ntu.ac.uk

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Abstract: Cold storage is an essential operation for many food products in cold supply chains. The main objective of this kind of storage is to preserve the food products for a certain period of time. However, often due to a lack of accurate technology, humidity and temperature in food storge are not monitored in real-time, which will affect the food quality. At present, the Internet of Things (IoT) has become a very popular choice for businesses in food supply chains. This is mainly because of the easy availability of internet, which helps monitor and control the quality of food in storage and transport. In this paper, the experiences of adapting and testing IoT sensors and Big Data technology for reducing food waste in a frozen food manufacturer in the UK are presented. The temperature and humidity monitoring within the operations of this ready-to-eat frozen meal company are also expected to maintain food quality and adhere to legal food safety requirements. Our reflection of experience gained in the installation of the sensors, collecting the data to a cloud server, and conducting data analytics with the data are also described. During the implementation of the technology, the company was able to identify optimal and non-optimal storage conditions for their food products and pre-processed ingredients. This allowed the further development of an alert system and corrective action protocol assisted using the technology installed. Results of the case study evidenced and reported a thorough real-time monitoring system that was able to reduce food waste and assure product quality, which could be applied in different stages of the food supply chain. This case can influence several food businesses to start adapting technology in their routine operations to ensure food quality and safety.

Keywords: cold supply chain; food waste; IoT technologies; temperature control; read-to-eat meals

1. Introduction

One-third of all food produced for human consumption is wasted globally, and this can occur anywhere along the food supply chain, which includes production, processing, distribution, and consumption [1]. This is not just a waste of important resources; it is also an affront to the 815 million people worldwide who are malnourished [2]. How can we address the issue of food waste while also improving food availability?

Maintaining a continuous cold chain, and the adequate temperature conditions along each step of the supply chain, is a potential alternative to save food from becoming waste [3]. This may be enough to feed many people globally if supply chains were modified to guarantee that food reached those who needed it the most. The cold chain is a variation on traditional food supply chains, and it refers to the movement of perishable goods that need to be refrigerated along each stage of the chain [4]. However, as supply chains get longer and more complex, they are frequently unable to cater to the specific climate needs of diverse items [5].

In this way, food providers may benefit from using revolutionary digital technologies, such as the Internet of Things (IoT), to optimise the supply chain and reduce food waste [6]. IoT combined with Big Data servers can store billions of data points, process data streams in real-time, and create workable insights [7]. For instance, data analytic tools can forecast models to predict inventory, consumer demand, and the probability of spoilage.

In the past, battery-operated thermometers or other passive temperature sensors were used to monitor the conditions of food products. Now, companies can ensure not only that food is handled under ideal climate conditions, but also that they are receiving temperature data in real-time [8]. Using IoT technologies can remotely monitor the climate conditions in different stages of the supply chain in real-time, identifying suboptimal environmental conditions for the company to tweak [9].

In this paper, we describe the experiences of adapting and testing digital technologies such as the Internet of Things sensors and data analytics for saving food waste in a frozen food manufacturer in the UK. The company in focus in this paper is Yumchop foods. It is a small and medium enterprise (SME) based in Northampton, UK. Yumchop are an innovative family-owned business who prepare frozen food and provide nutritious meals to customers in minutes via integrated microwave vending machines. They also provide a home delivery service via online purchase. Ready-to-eat meals are a convenient option that has been growing in recent years [10,11]. We describe our experiences of installing the sensors, collecting the data to a cloud server, and conducting data analytics with the data. The overall purpose of the entire exercise is to reduce food waste in the company, and thus increase overall sustainability.

1.1. Yumchop Foods

Although many consumers enjoy eating 'home-cooked' meals, not all like the process involved in meal preparation or the time it takes to cook. As lifestyles become increasingly busier, consumers limited in time are looking for alternatives to home-cooked meals. Yumchop Foods, a family-run business, has developed a vision to meet this need. Ready-to-eat meals are a convenient option that has been growing in recent years [10,11]. Yumchop was founded in 2016 in the UK out of a passion for food and a wish to introduce African flavours to British cuisine. Yumchop was founded in 2016 in the UK out of a passion for food by Mr. Michael Adewunmi Adefisan and Mrs. Abiodun Aderenle Adefisan, proud founders of this innovative hot-cooked meals food business. Today, Yumchop is a food manufacturing business specialising in frozen ready meals, prepared and served hot through automatic vending machines. Yumchop also provides a home delivery service via online purchase. Their mission is to create African meals that combine multi-cultural traditions, responsibly sourced ingredients, free from any added preservatives, colourings or flavourings, provided within environmentally friendly recyclable and biodegradable packaging [12].

1.2. Study Aims and Objectives

This study aims to understand and explore integrating temperature monitoring and Big Data technology within the operations of ready-to-eat frozen meal company Yumchop Foods. Using these technologies, we aim to reduce food waste, maintain food quality, and adhere to legal food safety requirements. This study explored the possibilities and purposes of available technologies that could meet these requirements using a case study approach. The experiences of installing the sensors, collecting the data to a cloud server, and conducting data analytics with the data are also described. The overall purpose of the entire exercise is to support reducing food waste in the company, and thus increase overall sustainability.

2. Drivers of the Frozen Food Industry

The modern retail scenario has seen a sharp rise in the use of frozen food products. There are a number of reasons for such a trend, as discussed below.

- Retaining freshness: In recent years, it has been revealed that freezing food when it is fresh could lock in nutrients and preserve flavour. This is one of the main reasons to consider buying frozen products over fresh: frozen fruits and vegetables can be more nutritious, cheaper and have better quality. In addition, frozen food also has a longer shelf-life [13,14]. Regarding nutritional value, fresh fruits and vegetables commonly lose nutrients, vitamins, minerals, fibre and antioxidants over time because they are picked before ripening, which gives them less time to develop a full spectrum of vitamins and minerals. Ripening may still occur during transportation, but these products will not have the same nutritive value as if they had been allowed to ripen fully on the farm. In addition, fresh fruits and vegetables are packaged, stored, transported and stored again (Figure 1a), and the exposure to storage and transportation periods at temperatures above freezing can negatively affect the nutrient quality [15,16]. Furthermore, during the long distance from farm to the consumer, fresh fruits and vegetables are exposed to light, heat and/or oxygen, which degrade some nutrients, especially vitamins [17].

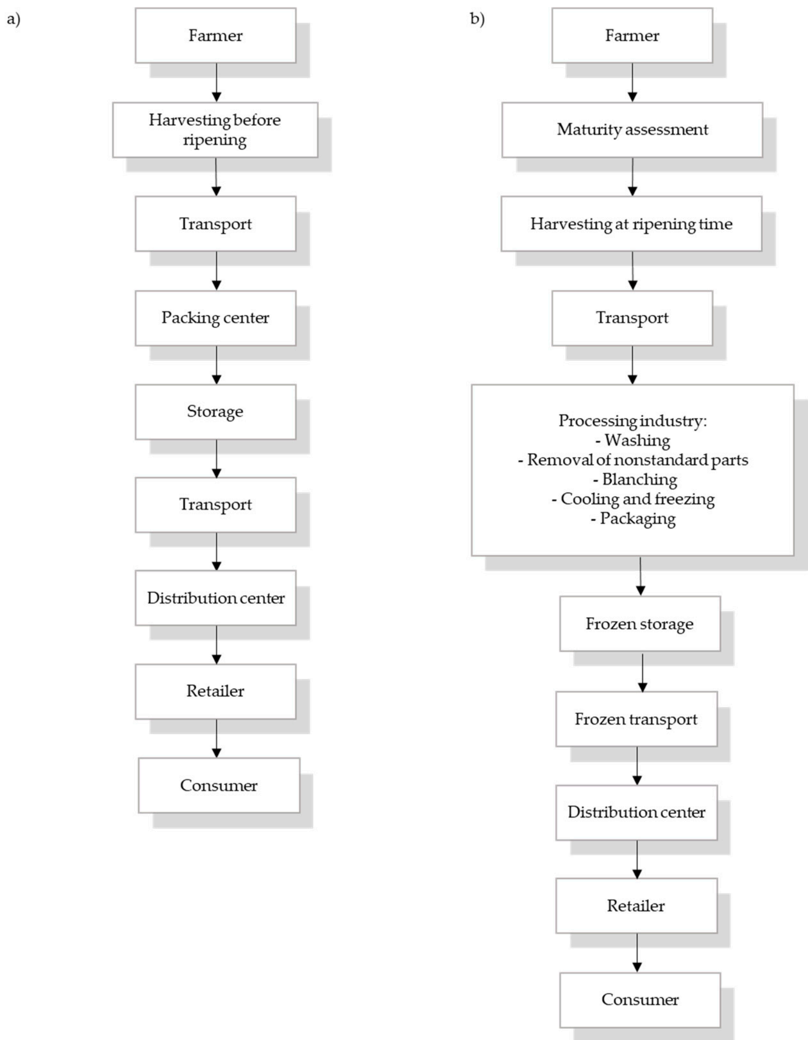

Figure 1. Product flow for: (**a**) fresh food; (**b**) processed frozen food.

- Retaining nutrients and anti-oxidants: On the other hand, frozen products are picked at peak ripeness (a time when they are usually the most nutrient-packed), blanched in hot water and then frozen (Figure 1b), which means they may retain more nutrients and antioxidants than fresh produce, despite the losses of water-soluble vitamins that may take place [18–20]. The blanching process is used to stop food-degrading enzymes and kill all microorganisms present in the food. This process can cause some water-soluble nutrients, such as vitamins C and B, to break down or leach out, but the subsequent freezing process locks the vegetables in a nutrient-rich state. However, Li et al. (2017) observed no significant differences in vitamin content between fresh and frozen vegetables [14].

- Availability beyond seasons: Fresh products can be limited, mainly during winter, which forces many consumers to turn to cheaper frozen options. Frozen food may be more cost-effective, as frozen fruits and vegetables come from an area where they are in abundance and there is a very low spoilage factor due to short transportation time between harvesting and processing, with these savings passed on to the consumer. Usually, frozen foods can be 50% cheaper than fresh foods, and since they can be stored for long periods without spoiling, the consumer can reduce food waste and the cost of having to put fresh products that have spoiled before their consumption in waste disposal [21]. In addition to quality and economy, frozen foods also have the advantage of convenience. Storing or buying frozen fruits and vegetables is the easiest way to get in all your recommended servings of fruits and vegetables per day.
- Role of packaging: Frozen foods are commonly packaged before storage and retail. Packaging fulfils many essential functions for food preservation. It protects food from detrimental physical, chemical, and biological influences, such as the effect of oxygen, light, moisture, odours and contamination by pathogenic microorganisms, extending food shelf life [22,23]. Food packaging also protects food from being lost or wasted through deterioration, spillage, and mixing of different products. The function of processing and packaging becomes even more critical when it is related to fresh products, which are highly perishable, mainly due to their high-water content and close-to-neutral pH [24,25]. Thus, such products require immediate processing to retain their safety and quality while ensuring safety for consumers [24].

The quality of frozen foods depends on the quality of raw materials used and the ability to maintain the food temperature at a suitably low level in any part of the food supply chain [26]. Fruits and vegetables are the most sensitive products to storage deterioration and should be stored at a temperature of −5 °C in moisture-proof, gas-impermeable plastic or freezer wrap for a maximum of 5 months in order to maintain their preservation [26,27]. Storing food in the freezer in good conditions is the best chance to prevent foodborne illnesses. Poor storage conditions along the supply chain and longer storage time can also reduce the quality of most fresh foods and result in food loss and waste (FLW) [28]. Therefore, it is essential to make demand forecasts in order to avoid products remaining unsold in storage before the recommended shelf life [1].

Ready-to-Eat Hot Meals

Ready-to-eat (RTE) hot meals are commercially available food preparations that require minimal cooking or processing before consumption. RTE provides convenience to customers due to the little time and effort needed in their home use. Additionally, RTE are generally easy to handle and store and have an extended shelf-life depending on their packaging and preservation method (e.g., frozen ready meals) [29]. They are available in retail in various forms—canned, vacuum-coated, or retort—and they can be found in the form of precooked, partially cooked, uncooked, frozen, or preserved foods. These products are, finally, consumed in households after minimal cooking. RTE commercial preparations involve meat, pastry, vegetables, fish, or seafood [11].

As mentioned earlier in this section, the demand for RTE meal products has been growing steadily over the past years, especially during the COVID-19 pandemic outbreak. A factor commonly attributed to this growth is an increasing trend for people worldwide to adopt busier, faster lifestyles. Moreover, recently, the COVID-19 pandemic and lockdown measures implemented by national authorities have increased the demand for hot ready meal products as an alternative to restaurants and other dining-out businesses [29]. Another factor contributing to this rise in the demand for RTE meals may be attributed to a growing interest in new products. Apart from their own national cuisine, people are keen to try meals from other cultures or ethnicities that they would not otherwise prepare at home. Therefore, a preference for ethnic food has driven the demand for these food products.

In 2019, the global revenue of RTE meals was USD 98.12 billion, of which Europe represented the most significant market with 40% of the share (USD 29.83 billion). Estimations show that the global revenue will reach USD 122.95 billion in 2024 (USD 39.36 billion in Europe) [10]. Projections estimate that the RTE market will grow at a Compound Annual Growth Rate (CAGR) of 4.62% during the forecast period (2021–2026) [29].

3. Processing Stages of Ready-to-Eat Meals

3.1. The Freezing Process

RTE meals are found in various forms in the market. Among these forms, frozen RTE products are a widely chosen option due to the advantages of freezing as a preservation method. When referring to freezing, the term is used to define the process in which food temperature is lowered below its freezing point, while frozen refers to the subsequent state kept throughout the rest of the cold chain [30].

Freezing is a long-established food preservation method applied to numerous goods, e.g., fruits, vegetables, meat, fish, etc., due to its effectiveness in retaining valuable properties such as taste, appearance and nutritional value, while extending product shelf life and preventing waste [30,31]. The process of freezing involves three stages; cooling the liquid-state product to its freezing point (pre-cooling stage), removing the latent heat of crystallisation during the phase transition (phase transition), and cooling the solid-state product to the final storage temperature (tempering stage) [31]. Freezing extends the shelf life of products considerably as the low temperatures and limited availability of liquid water slows down chemical reactions, such as fat oxidation, and inhibits the growth of microorganisms [31,32]. However, it is worth noting that freezing also causes physical changes to food. When freezing occurs, the water found in food forms ice crystals. Ice crystal formation, together with water movement within the food to join the developing crystals, can cause disruptions to the food structure [30,32].

Food to be frozen contains water interacting with different molecules. This way, some of the solid components may be found in solution with water, e.g., sugars and salts, while other water molecules are bound to components such as proteins. Other components have minimal interaction with water, e.g., fat [32], due to their hydrophobic nature. Given these different chemical interactions with water, and the formation of ice crystals that further concentrate the solution, freezing does not occur at a unique freezing point but rather over a range of temperatures. In general, below -10 °C, only the bound water remains unfrozen, and the food can be considered fully frozen [32].

After the freezing process, frozen food can still undergo physical disruption as water continues to transfer internally, i.e., small ice crystals migrate to form larger crystals. Temperature fluctuations can further increase this process during storage [32]. The larger the crystals are, the more significant the physical disruption on cells and tissues that they will cause when the product is thawing. This process is known as drip loss, which often results in frozen products having less quality than fresh food of the same type due to a loss of firmness and flavour [33]. Faster freezing times generally favour the formation of smaller, less damaging intracellular ice crystals, whereas slower freezing rates tend to result in more extensive and extracellular ice crystals. Prolonged frozen storage, especially if the storage conditions are poorly controlled, will diminish the benefits of faster freezing over time. Overall, frozen foods are usually perceived as having quality very close to that of fresh foods and their convenience due to their long shelf life provides a key advantage for many consumers.

Although freezing is a relatively old method for food preservation, technological advancements have allowed faster freezing processes to reduce the size of ice crystals and, thus, minimise the physical disruption in the structure of food and improve overall product quality. Emerging technologies focus on improving heat transfer efficiency and control over ice crystallisation even further [31]. The leading freezing technologies can be found in Table 1 [31].

Table 1. Freezing technologies and main characteristics.

Freezing Technologies	Characteristics
Air-blast freezer	The products are frozen in a blast of circulating cold air at a temperature between −35 °C and −45 °C under forced circulation. Typically, the freezing time varies from 12 to 48 h.
Tunnel freezer	The products on trays are placed in racks or trolleys and frozen with cold air circulation inside the tunnel at a temperature of −35 °C.
Belt freezer	It was designed to provide continuous production of precooled air flow at approximately −40 °C with the help of a wire mesh conveyor inside the blast rooms.
Fluidised bed freezer	These are modified blast freezers in which air between −25 °C and −35 °C is passed at a high velocity (2–6 m/s) through a 2–13 cm bed of food, contained on a perforated tray or conveyor belt.
Contact freezer	The product being frozen is fully surrounded by the freezing medium, the refrigerant, maximising the heat transfer efficiency.
Immersion freezer	The food is passed through a bath of refrigerated propylene glycol, brine, glycerol or calcium chloride solution on a submerged mesh conveyor.
Indirect contact freezer	The products being frozen are separated from the refrigerant by a conducting material, usually a steel plate.
Plate freezer	These freezers consist of a vertical or horizontal series of hollow plates, through which refrigerant is pumped at −40 °C temperature.
Cryogenic freezer	These freezers use solid or liquid carbon dioxide or liquid nitrogen directly in contact with the food, and refrigeration is obtained as a pre-cooled substance. The food is exposed to an atmosphere below −60 °C.
Liquid nitrogen freezer	In these freezers, the food travels on a perforated belt through a tunnel where the product is cooled by gaseous nitrogen and frozen by liquid nitrogen spray at −196 °C.
Liquid carbon dioxide freezer	Used as a pre-freezing treatment before the product is exposed to nitrogen spray.

Other methods for food preservation include, but are not limited to, thermal processing, dehydration, refrigeration, extrusion and irradiation [34]. While each of these methods may confer advantages depending on the use case, freezing has been reported as one of the most widely used for food preservation. In fact, the frozen food sector represents a large part of the food supply globally [32].

3.2. Food Preparation and Quality Assurance

Typically, all frozen food and ready meal businesses try to sell their products with a well-focused marketing strategy such as quality assurance, freshness, and nutrient count. RTE food companies claim their food as a high-quality product by making crucial claims: either quickly frozen to lock the ingredients, or freshly packed/prepared and frozen in a short period to lock/preserve the taste [35].

Local sourcing is one of the main drivers to prepare the food quickly to freeze within a few hours of preparation. The UK Government is supporting British farming businesses through different options such as encouraging owning or leasing agricultural land [36], creating demand in the local market. Leading UK retailers, namely Tesco, Sainsbury's and Morrisons, support British farmers with long-term supplier contracts and by offering premium prices for local produce. This support is extended especially for local produce such as milk, carrots, potatoes, cabbages, and apples.

As discussed above, the ingredients should be sourced locally because the processing plant requires a constant supply of raw materials to keep the freshness of the frozen products. The products are manufactured in frozen food processing plants where the fresh foods are processed at very low temperatures. At the processing plants, the raw materials (fresh foods) are sent for manual inspection and sorting, where workers cut the valuable part of a food and discard the part which is not suitable for consumption [37]. This sorting process helps to maintain the size and integrity of the fresh food.

After the sorting process, the fresh food is dropped into fresh water, where foreign materials such as soil and dust are washed away. The typical next step in the frozen processing plant is the blanching and cooling process, which helps deactivate enzymes in the food and maintain the colour of the fresh food. The fresh food is moved to a heated container where heated water is sprayed on top of the raw material (vegetables or meat) for a short period [37]. Once the food is heated, it is transferred to cool containers with cooled water ranging from 10 to 14 °C to low temperature. After this process, the excess water must be removed from the raw material to prevent any extra ice layers while freezing. The dewatering process transfers the food to a vibrating conveyor to shake off any excess water. The food is then transferred to individual quick-freezing units, and the food is maintained at freezing temperatures.

In the United Kingdom, according to the guidelines provided by the Foods Standard Agency, fridges and chilled display equipment should be set at 5 °C or below to make sure that food is kept at 8 °C or below. As for control of the temperatures, fridges and chilled display equipment need to be checked at least once a day, starting with opening checks. For frozen food, the guidelines outline that it is good practice to keep frozen food at −18 °C or colder. Food labelled as 'quick frozen' must be stored at −18 °C or colder or displayed at −12 °C or colder. In this case, it is mandatory that the temperature of the freezing equipment should be checked at least once a day [38].

4. The Role of Digital Technologies in Reducing Food Waste in Agribusiness Supply Chains

In the food industry, staying in step with technology has become essential for improving business processes. Technology helps food manufacturers to produce more efficiently. Processes such as labelling, IoT traceability, food safety, and understanding general food trends can all be improved significantly through the integration of technology [39]. Improving shelf life and food safety revolves around technology, ensuring affordability and consistent quality.

With a supplier network that has become increasingly global, food companies need to detect changes and react quickly to things such as health threats. We may see new technologies such as Artificial Intelligence (AI) and the IoT play a more prominent role in food traceability and transparency [40,41]. Food businesses will also need to remain compliant; e.g., in the USA, the Food and Drug Administration (FDA) continues to update its Hazard Analysis Critical Control Point (HACCP) guidelines. In addition, record-keeping will be required to be kept in an electronic format, as stipulated by the FDA's Food Safety Modernization Act (FSMA) [42]. Overall, food companies should expect the FDA to place greater importance on technology-enabled food safety requirements. Organisations should try to adopt robust technology systems sooner rather than later so that they have time to try out the right technologies instead of rushing in order to remain compliant.

The food supply chain is an elaborate but essential food production system required by the global community to maintain food security. Though the food supply is typically taken by most for granted, just one disruption in the chain can lead to shortages, poisoning, or increased prices. While solutions are in place to streamline the global food supply chain, there are still several problems facing the food systems industry in Europe, particularly due to the coronavirus pandemic and Brexit [43]. Some of the problems that have become most dominant are farming labour shortages, poor communication between supply chain participant organisations (also due to a lack of common standards and protocols for information exchange), growing regulations, consumer demand and complexities in inventory and labour planning due to COVID-19 and Brexit. Moreover, a lack of visibility, communication among participants, and intermittent COVID-19 restrictions have put restaurant businesses and their suppliers in challenging positions [44].

For many fresh food producers, reducing food loss and waste (FLW) is a great concern due to its high socioeconomic costs, relationship to waste management, and climate change challenges [45]. FLW has indeed become an issue of great public concern. The 2030 Agenda for Sustainable Development reflects the increased global awareness of the problem, with Target 12.3 calling for reducing food waste along the production and supply chains [46]. The percentage of FLW varies between food sectors, being incredibly high for the fresh produce supply chain: around 50% of all fruits and vegetables are disposed of in the EU each year [47]. About one-third of fruit and vegetable waste is caused by produce perishing between being harvested and reaching the consumer, largely due to long distribution routes and inadequate technologies used in transport and storage.

Recently, digital tools (e.g., sensors, food apps) have become a viable solution for FLW recovery [48,49]. However, the literature related to understanding how these technologies can contribute to reducing FLW is limited [45,48–53]. According to Irani et al. (2018), technologies can influence the FLW within the broader food security landscape [51]. Digital tools can also facilitate the development of alternative food networks that can modify the traditional linear food chain [50]. According to Kamble et al. (2019), the application of the IoT, for example, can support actors to control FLW by monitoring food quality, managing food close to its shelf life and improving the management of inventory and store layout [52]. Sensor technologies can also help reduce FLW through administering the right physical environment, especially concerning temperature and humidity.

In the context of frozen food storage, temperature fluctuations can induce disruption of physical changes within the food structure. This necessitates continuous monitoring of temperature and taking action before the temperature fluctuation exceeds a suggested range. This case study article specifically looks at how these digital technologies are helping Yumchop to reduce FLW through sensor technology and cloud data analytics. This is further explained in the next section.

5. Yumchop and the Digital Technologies

Yumchop specialises in frozen ready meals based on flavoursome authentic world foods with an African twist. They offer a varied list of meals available through online purchase and automatic vending machine, currently with 15 meal options. Their meals are frozen to retain freshness, whilst minimising waste. A fundamental part of their revenue comes from distributing ready meals at institutions such as universities and medical facilities through automated vending machines. These unattended retail kiosks are fitted with an integrated microwave which warms the food upon purchase. However, Yumchop also delivers food to their customers' homes through direct purchase at their website, enabling one-off purchases and monthly subscriptions that customers can customise to receive food at their preferred intervals. The products and prices are relatively standardised, with an availability of multiple buy options (bundles and monthly subscriptions). Moreover, they also supply directly to retailers and large organisations.

Yumchop Foods currently operates in agreement with universities, such as Imperial College, London, through the approved Innovative Food Framework—The University

Catering Organisation (TUCO)—and the National Health Service (NHS) as part of the NHS Food Framework agreement to supply ready meals in hospitals and healthcare settings. As seen on the TUCO website, their route-to-market strategy is via unattended retailing kiosks that they utilise as a platform to offer 24 h access to their meals and that can be deployed into different sectors of the economy, i.e., universities, warehouses, serviced offices, hospitals.

5.1. Operations of Yumchop

Yumchop uses locally sourced raw materials to prepare their ready-meal products. Their production process can be seen in Figure 2. Most of the ingredients are supplied by local vendors, located within a radius of 20–30 miles from the Yumchop production plant in Milton Keynes, UK. Meat (chicken and lamb) is transported in temperature-controlled logistics and stored in cold storage as soon as it arrives at the production site. The meat products are marinated and prepared for the next two days before they are fully cooked. Once the food is cooked and ready to be served, they are delivered to the consumer or sent to the vending kiosks. Some food is also stored in frozen racks to be sold as frozen ready meals. Yumchop uses organic ingredients for marination, such as organic coconut oil, whilst no artificial colours, flavouring or chemicals are used.

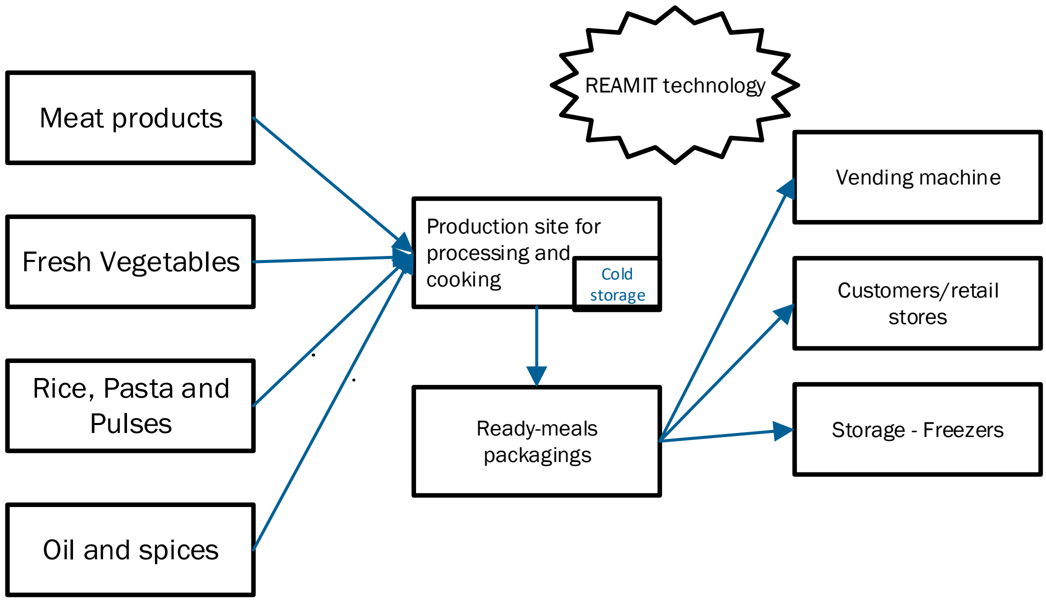

Figure 2. Yumchop processing diagram.

5.2. Food Preparation and Storage at Yumchop

Once the food is sourced from local suppliers, ingredients are prepared for cooking. Fresh vegetables are washed and diced to the required shape using a dicing machine and are then stored refrigerated. For example, the dicing process takes about 5 h for 100 kg of peppers, which are then packaged in 5 kg bags and kept within a refrigerator. Meat is instantly marinated with oil and spices, and then refrigerated to avoid bacterial growth. Fresh meat and vegetables are cooked and then sealed in packaging within two days of arrival in the kitchen. Rice and pulses are stored in a dry storage area. Although the cooking of rice is a straightforward method, there is some wastage during its cooking process. For example, 30 kg of rice can make up to 80 kg of cooked rice, however, 8–10% of this cooked rice is wasted due to sticking at the bottom of the pan. All finished products are put in a blast freezer for 2 days within 3 h of cooking. Fully prepared meals are stored in a freezer with the temperature from −24 °C to −18 °C. All products are transferred to an internal freezer located within the production processing plant in 20 ft containers. Yumchop also has 40 ft backup freezers located outside the plant, to have enough supply to meet any high demand.

5.3. Food Delivery via Vending Machines

Yumchop delivers the food via vending machines installed in selected rail stations, hospitals and universities. Each vending machine can hold up to 75 packs of RTE meals. Yumchop replenishes its stock in the vending machines when it goes below 25 packs. Their planning cycle for production is calculated eight times higher than the demand. This creates a good balance between the supply and the demand. The product expiry date is 12–24 months from the production date when it is kept in a controlled temperature range of −18 and −24 °C. However, the company ensures that no product spends more than 6 months in the freezer. This highlights Yumchop's commitment to safety and quality, which, in turn, assures the high standards of their products.

5.4. New Digital Technologies for Yumchop

Following a confidentiality agreement, the REAMIT project team started implementing appropriate digital technologies for Yumchop to ensure that frozen food and raw materials for preparing the food are stored in the right temperature in the frozen food manufacturer's factory.

These technologies have been integrated into Yumchop's operations, from storing the raw materials and prepared foods in the internal storage, through to RTE meal packages being stored in the retail vending machines. Sensors monitor the temperature of the environment at each stage of the operations, including sourcing, preparing, storing, logistics and delivering to customers. These data are transmitted to the Yumchop team. This is achieved through dashboard options, with Yumchop's dashboard data sending alerts to the team if the temperature drops below −18 °C. This alert helps the company fix any malfunctioning of the fridge/freezer before stored items become spoiled and wasted.

6. Implementation of the Technologies

Yumchop manufactures and supplies high-quality frozen food through vending machines to consumers. In the year 2021, one of their warehouses experienced a sudden and undetected rise in temperature throughout the night, and the company could have had a significant loss of its stock from the frozen food storage. However, human intervention occurred on time, before significant losses. As the temperature monitoring was not automated and carried out only through regular manual inspections, temperature drops have led to spoilt food quality, which meant the food was discarded as waste. Yumchop's manual monitoring and controlling system of temperature within production, storage, and delivery systems needed a considerable proportion of human intervention.

The two most critical parameters that Yumchop makes a priority to protect their consumer trust are the quality of supplied food and its taste. Any such unexpected incident makes integrating technology in their warehouses a natural requirement to avoid any further loss to the organisation. This is not just crucial for maintaining the quality of food and its taste, the two most vital parameters for food, but it is also critical to streamlining the business for a growing consumer market with high expectations of quality assurance.

Having appropriate technological solutions in place could save food manufacturing and supply companies a significant amount of money whilst helping to avoid waste. In this section, the existing business scenarios of Yumchop are considered to understand how a technology-based solution is helpful for the company to improve its efficiency. These solutions could prevent huge accidental losses of food. Moreover, rather than just avoiding the losses, these solutions can reinforce and strengthen quality assurance and enhance the company's credibility.

The architecture of technology implementation is summarised in Figure 3. Specialist sensors for measuring specific parameters as agreed with the company have been installed at various locations in Yumchop's factory. The sensors have been connected to a secure cloud server. These data have been accessed by data analytics partners. The data from the server can be monitored by Yumchop via a specially designed interactive dashboard. This dashboard is discussed in the next section. A special feature of the dashboard is the alert system. The upper and lower thresholds of the parameters to be measured have been fixed in agreement with the company. If sensor readings are consistently above the upper threshold or below the lower threshold for three consecutive readings, an alert is triggered and sent to the mobile phones of Yumchop.

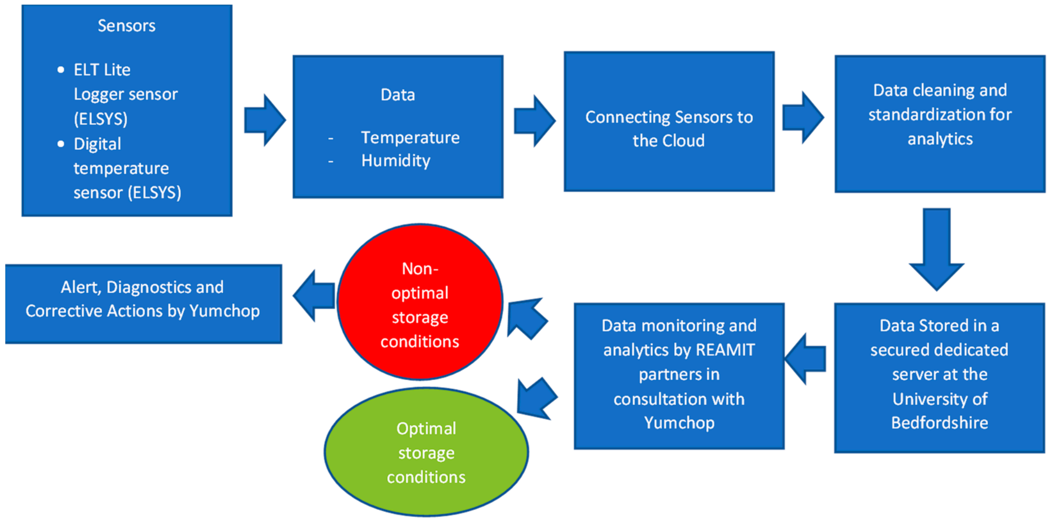

Figure 3. An architecture for implementing digital technologies for Yumchop.

These digital technologies can be useful to Yumchop in multiple ways. They help the company to support close monitoring of food storage in their factory. Large freezers are installed in the factory for storing incoming raw materials (vegetables, meat, etc.) and for storing the frozen processed food. There are plans to expand the technology to monitor temperature in vending machines and also for when the frozen food is transported in trucks from the factory to vending machines.

Monitoring Conditions of Food Storage within Yumchop's Premises Using Technology

Based on the nature of the RTE industry, Yumchop has a legal obligation to monitor the temperature of the surrounding environment in which the frozen food is kept by the company at least twice a day. The company is regularly audited to ensure all the regulations are followed at its premises. There are fines and other legal penalties if the company is found to violate this legal regulation at any point during its business. Thus, it is critically important for the company to measure the temperature of the frozen food's environment and always ensure that this temperature is within the permissible range so that the food is always of the highest quality. Currently, at Yumchop, the process of measuring the temperature twice a day is manual and dependent on personnel. The manual measurement process has multiple risks or disadvantages:

1. A significant delay is present in sharing the measured temperature information with the stakeholders and the actual occurrence of that temperature. The process is not in real-time. This exposes the system to a significant risk of not carrying out a corrective action in time if any undesired situation occurs;
2. It involves dependency on personnel. The temperature measurement involves additional overhead involving personnel and is subject to errors in measuring by a human;
3. Though manual measurement is taken twice a day, it does not measure the temperature at other instances in the day. The temperature fluctuations in the environment surrounding the food can happen in other instances due to any undesired cause.

Measuring the temperature only twice a day at fixed instances suffices the legal requirement but does not capture any potential risk to the food due to temperature changes (fluctuations) at other times;

4. Measuring the temperature manually does not provide scope for integrating the corrective action mechanism with the system in an automated way.

For these reasons, temperature sensors have been installed in the fridge and freezer areas, as presented in Table 2. This is also shown in the layout in Figure 4.

Table 2. Locations where temperature sensors were installed.

Equipment	Temperature Thresholds
Container—Cold room	Temperatures need to be <+5 °C.
Green kitchen—Fridge	Temperatures need to be <+5 °C.
Zone B—Freezer 1	Temperatures need to be between −24 °C and −18 °C.
Zone B—Freezer 2	Temperatures need to be between −24 °C and −18 °C.
Zone D—Cold room freezer	Temperatures need to be between −24 °C and −18 °C.
Zone D—Cold room fridge	Temperatures need to be <+5 °C.
Zone D—Fridge	Temperatures need to be <+5 °C.
Zone E—Fridge	Temperatures need to be <+5 °C.
Zone E—Freezer	Temperatures need to be between −24 °C and −18 °C.
Vending machine	Appropriate temperature (as suggested in the pack)

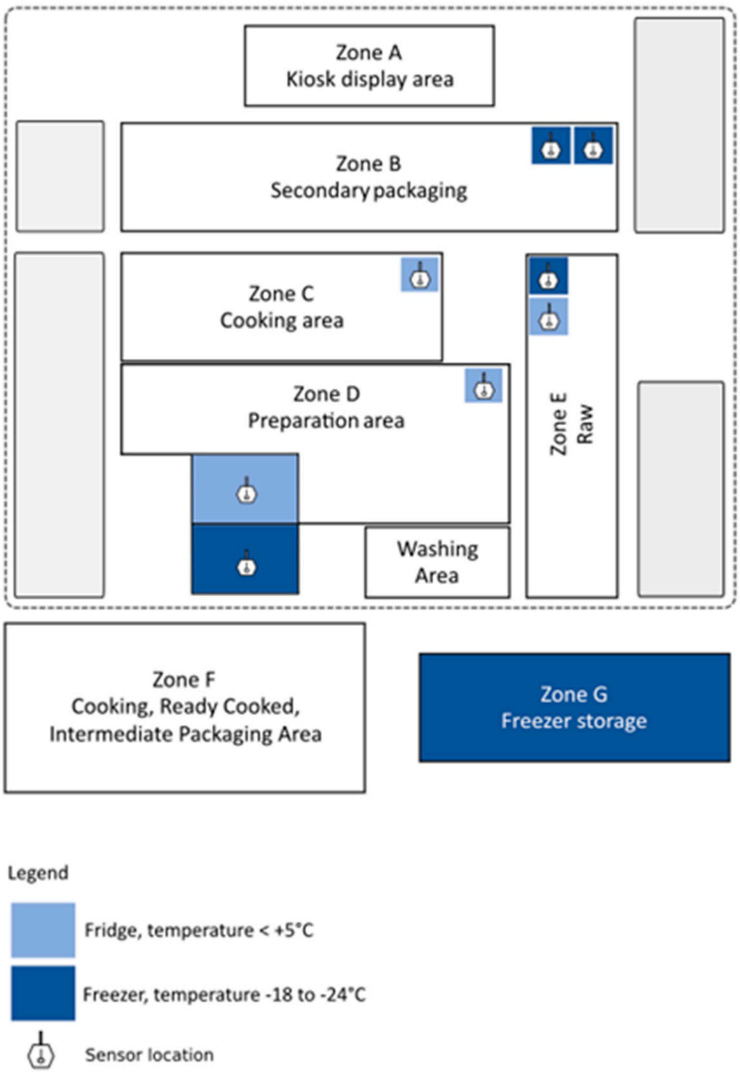

Figure 4. A layout showing the locations of sensors in Yumchop's premises.

As the company needed a customized solution to their temperature-controlled locations, the REAMIT project installed IoT sensors in the areas specific to cold containers, fridge freezers, in different zones as mentioned in Table 2 and Figure 4. Each sensor installed at Yumchop has its own rule-based alerting algorithm using different threshold temperatures depending on where the sensor is installed. Alerts are sent to Yumchop when two measurements in a row are over the temperature thresholds shown in Table 2. For example, notifications should be sent if the temperature in the container located in the cold room rises above 5 °C, while notifications for the freezers should be sent above −18 °C. This allows specific alerts to be sent to staff phones with exact information of the problem at the factory. To avoid false alarms, alerts are only sent after 6 readings, 5 min apart are recorded above the threshold temperatures (30 min consistently above threshold temperature).

The alerting system is implemented using Amazon Simple Notification Service (SNS) and is built into the REAMIT dashboard. The dashboard for Yumchop shows the temperature in all zones at Yumchop where sensors have been installed (Figure 5), as well as the thresholds for the gauges (red-orange-green). The temperature thresholds can be set according to Yumchop's needs. For example, with reference to Figure 5 of dashboard readings, if the pointer in the meter dial is within the range of the green zone, no action is needed. If the pointer is in the orange zone, caution is essential to be ready to tackle problems. If the pointer is in the red zone, immediate action is required from the operations team of the case company. Preset alerts from the system will help to monitor the temperature to ensure quality.

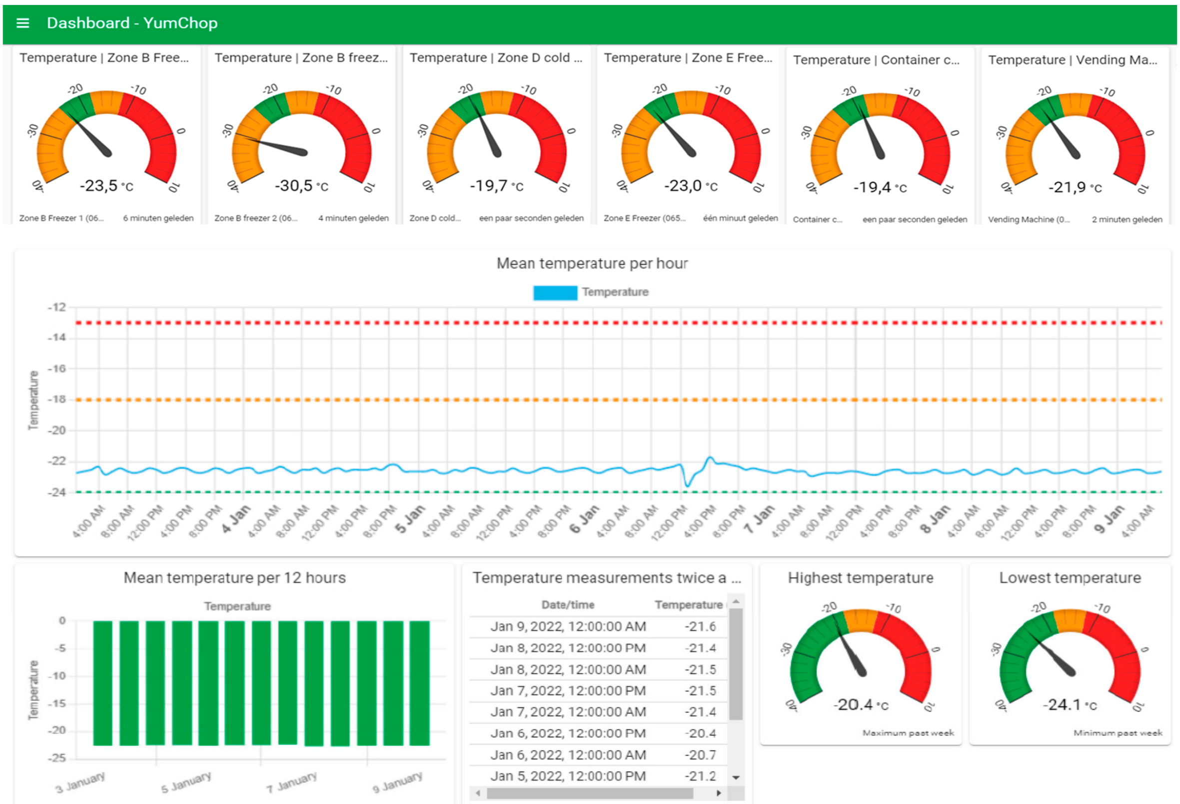

Figure 5. Yumchop's sensor dashboard from sensor data (setup by Dutch partner who follows European numbering).

Having the facility to measure the temperature automatically in real-time would not just eliminate all the above risks and disadvantages but would also significantly help the company in improving system efficiency, monitoring and improving the quality of food, bringing more transparency, saving manual labour overhead, and eliminating any food loss due to temperature fluctuations.

7. Sustainability Benefits of the Technology Solutions

This case study outlined our experience working with the Yumchop company to install and run sensors and provide data analytics. Food loss and waste is a significant concern for the company, which identified three main types of food storage areas susceptible to food loss: cool, chill, and frozen areas. The use of digital technology has helped Yumchop in multiple ways:

1. Reduced food waste: The idea of continuously monitoring the temperature of stored food products and sending out alerts in the case of any issue can potentially help to reduce the chances of food becoming waste by taking rapid corrective actions;
2. Ensuring the quality of food: Our records have so far indicated that the temperature have been kept at optimal conditions after the technologies have been installed. Such a record improves the perception of the quality of the food and the company can be more confident in marketing its food products. In addition, it could boost frozen ready-to-eat food quality due to an improved production process;
3. Legal compliance: To follow the legal, regulatory requirements, the company needs to record the temperature in each area twice a day, which was carried out manually until now. As demonstrated above, the automatic temperature measurement is critical in cool rooms and other areas. At such locations, automated technology could be significantly used to measure the temperature in an automated way and take corrective actions;
4. Improved revenues for the company: Since the company is more confident of the quality of its produce, there is a chance that it can price its products at a premium, increase its sales and thereby generate more revenue;
5. Reduced emissions: Measuring the storage temperature does help at times to optimise energy consumption. For example, if temperature settings in fridges or freezers are set too low for the optimal range, there could be unnecessary energy consumption. This situation can be avoided while monitoring the dashboard. This can help reduce environmental impacts. In addition, there is a more positive impact on the environment because (i) avoiding food waste helps to avoid greenhouse emissions as the food was not sent to landfill; and (ii) there is a saving of resources that go into the production of the food that is prevented from being waste;
6. Improved green image for the company and overall improvement in sustainability: We alluded to the economic benefits and environmental benefits in the previous points. There is also a social element here, because food waste avoided can be used to feed those in need of food. Overall, using technology for reducing food waste helps improve the green image of the company alongside transparency in its processes, which would be highly useful for senior stakeholders in the company. This, in turn, results in strengthening the company's brand value and trust among customers;
7. Other benefits include saving cost and reduced dependency on manual labour, which has a higher importance due to the shortage of manual labour in the UK after Brexit and during the COVID-19 pandemic period;
8. Regulatory compliance: the UK food sector is urging businesses to adhere to and maintain specific temperature thresholds. Yumchop Food has mentioned this aspect of regulation as the motivation for their involvement in the REAMIT project.

> *"In terms of our relationship with REAMIT and what motivated us to work with the project was around the legal requirements as a food manufacturer to ensure that we keep monitoring our freezers and to ensure that our freezers are meeting the required threshold of -18 degrees and the fridges are meeting the required legal threshold. It's also to ensure that we minimise waste."*

8. Discussion, Contribution and Conclusions

During the implementation of the technology, Yumchop was able to identify optimal and non-optimal storage conditions for their ready-to-eat frozen food products and pre-processed ingredients. This allowed for the development of an alert system and corrective action protocol assisted by the use of the technology, including temperature and humidity monitoring sensors, and data analytics. Results of the case study have allowed for a thorough monitoring system, compared to the manual checks which took place prior to the project. It has been demonstrated that Yumchop can reduce their food waste and assure product quality through the use of innovative technology, which can be applied elsewhere within both RTE food production and throughout the food supply chain.

A key concern for producers, suppliers and retailers in the food industry is preserving the quality and freshness of food throughout the supply chain without suffering any food loss and wastage. This is even more critical and challenging for the cold and frozen food industry due to the food's highly perishable nature and the regulations involved, where cold storage is an essential operation and there is always a risk of food wastage due to malfunctioning of the equipment. Incorporating new Industry 4.0 digital technologies such as IoT sensors and Big Data analytics provides a natural solution for food systems to address this challenge by offering real-time monitoring and alerting systems for factors affecting the food quality, such as temperature and humidity, and avoiding long downtime due to equipment malfunctioning. Apart from saving food and energy, it also offers other economic advantages to stakeholders by improving operational efficiency, reducing manual labour, strengthening the brand and customer base, rapid adaptation of regulatory requirements and supporting integration with other technologies for increasing competitiveness. In this paper, the experiences of adapting and testing IoT sensors and Big Data technology for reducing food waste in a frozen food manufacturer in the UK are presented. A key hurdle that holds back a lot of food businesses from adapting new digital technology and moving towards Industry 4.0 and sustainable food systems is uncertainty among the stakeholders about its true value addition in a cost/benefit perspective.

The Yumchop case study revealed actual value addition in their operations through REAMIT technology. Mrs. Abiodun Adefisan from Yumchop Foods mentioned as follows:

> *"So, it's really about that real-time solution that REAMIT Technology brings, it's that real-time value, you get the real-time data and you can make real-time decisions necessary for the business".*
>
> *"I think personally being involved with REAMIT, as an SME organisation that is growing, I believe for REAMIT to support us in a wider sense, that it will also have a positive impact in any other future projects that REAMIT or other program will look into, within the wider manufacturing setting in the UK. At least, they will have that data and have worked with us, it can be rolled out into other SMEs or companies on a bigger footing in terms of monitoring. Data monitoring in manufacturing is key, so I think it's also an advantage to REAMIT to really support us on this".*

This case can act as a reference and influence several food businesses to start adapting technology in their routine operations to ensure food quality, safety and transparency.

In the academic literature, empirical studies or modelling approaches are used to show the performance level of food companies. In this study, we have considered a live project installing IoT sensors and monitoring the food waste reduction in real-time. This article also explained the complexities of any food company with frozen and chilled storage facilities and the importance of using technology to maintain the quality. This is one of the new approaches in the academic literature. This case can influence several food businesses to start adapting technology as a new norm to ensure quality.

There are, however, some limitations; for example, using environmental sensors can only give full quality assurance for an entire batch of product, rather than for each individual product item. In future, spectroscopy to identify chemical composition within each food product could be undertaken using a handheld smart device at retail outlets.

However, in order for a handheld device to be used, additional labelling requirements such as a barcode for both price and sensor recognition would need to be produced and included on packaging.

Future research needs to include a study of the temperature of raw materials or processed food in fridges, the impact of seasonal variations—increase in energy costs during summer compared to winter—by linking with local weather data, and how the increased visibility of temperature in fridges helps Yumchop reduce their energy consumption. For example, the company realised that some freezers were cooling unnecessarily to −32 °C when −20 °C is sufficient. In addition, studying the patterns of alerts and corrective actions and how temperature records are used in supporting Yumchop's compliance with HACCP directive, alongside other regulatory frameworks related to food waste, would be useful.

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Article

A Case Study of Human Milk Banking with Focus on the Role of IoT Sensor Technology

Usha Ramanathan [1,*], Katarzyna Pelc [2], Tamíris Pacheco da Costa [3], Ramakrishnan Ramanathan [4] and Natalie Shenker [5,6]

[1] Nottingham Business School, Nottingham Trent University, Nottingham NG1 4FQ, UK
[2] Bedfordshire Business School, University of Bedfordshire, Luton LU2 8LE, UK
[3] School of Biosystems and Food Engineering, University College Dublin, Agriculture Building, UCD Belfield, D04 V1W8 Dublin, Ireland
[4] Essex Business School, University of Essex, Southend-on-Sea, Essex SS1 1LW, UK
[5] Department of Surgery and Cancer, Imperial College London, Du Cane Road, London W12 0HS, UK
[6] Human Milk Foundation, Rothamsted Institute, Harpenden AL5 2JQ, UK
* Correspondence: usha.ramanathan@ntu.ac.uk

Abstract: Human milk is the biological norm for newborn nutrition, with breast milk from the mother being recognized as the best source of nutrition for infant health. When the mother's milk is unavailable, donor human milk is the best alternative for infants with low birthweights. Growing recognition of the benefits of donor human milk has led to increasing global interest in monitoring and controlling human milk's quality to fulfil the need for donor human milk. In response to this need, the REAMIT project proposed to adapt and apply existing innovative technology to continuously monitor and record human milk quality and signal potential milk quality issues. IoT sensors and big data technology have been used to monitor conditions that may increase spoilage (such as temperature and humidity) in the transportation stage. The sensors were installed in the insulated bags used to transport the milk from the donor's home or hospital to the human milk bank and vice versa. The temperature and humidity were collected every 30 min, whilst the GPS locator sent data every 2 min. The data are collected in the cloud using GPRS/CAT-M1 technology. An algorithm was designed to send alerts when the milk temperature is above the prespecified threshold specified by the organisation, i.e., above −20 °C. The experience showed evidence that IoT sensors can efficiently be used to monitor and maintain quality in supply chains of high-quality human milk. This rare product needs a high level of quality control, which is possible with the support of smart technologies. The IoT technology used can help the human milk supply chain in five different aspects, namely by reducing waste, assuring quality, improving availability, reducing cost and improving sustainability. This system could be extended to various supply chains of rare and precious commodities, including further medical supplies such as human blood and organs, to completely avoid waste and ensure total quality in supply chains.

Keywords: human milk bank; IoT technologies; temperature monitoring; waste reduction

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1. Introduction

Human milk is the optimal source of nutrition for infants, providing thousands of compounds essential for development and nutrition including proteins, lipids and oligosaccharides, as well as immunological protection [1,2]. However, for various reasons, there are numerous circumstances in which mothers are unable to lactate or provide sufficient breast milk, particularly in the first days postnatally. In these situations, especially regarding vulnerable preterm and sick infants, donor human milk (DHM) from a human milk bank is considered the first-line source of nutrition where there is a shortfall of maternal milk [1]. Preterm infants fed with DHM have a lower risk of developing necrotizing enterocolitis (NEC) and late onset sepsis as compared to those fed with formula [1,3]. The

American Academy of Paediatrics and the World Health Organization (WHO) [4] both establish DHM as the most suitable replacement for neonates when the mother's own milk is unavailable [3,5,6], but as a cost-saving intervention operating at scale, milk banking would be a highly cost-effective public health intervention [7].

Human milk banks (HMBs) play a vital role by recruiting donors and processing, storing and supplying DHM to neonatal intensive care units (NICUs) and similar settings in a safe and controlled manner [8]. According to recommendations from the European Milk Bank Association (EMBA), donor screening should include an oral interview and a written health questionnaire followed by serological testing [3]. As for handling and storage, selected donors are advised to collect expressed milk for donation in a suitable container and requested to freeze it as soon as possible within 24 h. Once donated milk is received by the HMBs, it is stored in a freezer at −20 °C until thawed and pasteurised [9]. Microbiological testing is performed before and after pasteurisation (commonly 62.5 °C for 30 min), and milk is passed according to nationally agreed guidelines [3,10]. HMBs then distribute DHM to the required medical settings or families in the community facing breastfeeding challenges. Donor milk remains a costly option, the accessibility of which is sometimes limited [6,10]. For these reasons, donor human milk is considered a valuable and limited resource. In the scope of the present study, minimising DHM loss and waste could translate to enhanced quality and less milk wastage, increasing capacity of HMBs.

The Human Milk Foundation (HMF) is a non-profit charitable organisation working to create equity of access to assured supplies of DHM. The organisation works in several ways to secure human milk in order to protect vulnerable young lives, providing screened donor milk to sick, premature babies in NICUs and to mothers suffering from cancer and other conditions. As part of the HMF, the Hearts Milk Bank (HMB) was founded to provide equitable and safe access to donor milk in the UK, as well as supporting and facilitating research. It has served over 400 families and 10,000 babies with donor milk since its creation, and it has supported 53 hospitals and assisted with the delivery of 3943 litres of donor milk in the year 2021 [11]. This has created a huge social impact in saving lives of babies at risk. The lives of several thousand babies are being saved through the HMF's initiative of transporting human milk within the UK in a safe way to ensure quality.

Although continuous and deliberate efforts are already in place to ensure the safety of donor milk, the HMF have identified room for improvement during the transportation of donor milk to their final destinations within the UK. In collaboration with REAMIT, a transnational European territorial cooperation project co-funded by the Interreg North-West Europe (NWE) Programme aiming to reduce food waste (www.reamit.eu) (accessed on 1 December 2022), HMF uses Internet of Things (IoT) sensor technology to monitor the quality of DHM during transportation. Digital tools (e.g., sensors, big data and Internet of Things) have become a viable solution for food loss and waste recovery in recent years [12]. In this regard, such tools can also be implemented for continuously monitoring DHM quality parameters (e.g., temperature), allowing corrective action in a timely manner to mitigate loss.

As part of the HMF, the Hearts Milk Bank provides screened DHM to NHS hospitals and families facing feeding challenges, including delayed lactogenesis, breast development pathology, maternal cancer treatment and other conditions. Since 2017, Hearts has supported over 500 families and thousands of infants in over 50 NICUs with over 11,000 L DHM [13]. Logistics from the donor (collection point) to the newborn babies (delivery point) involve several stages including storage, pasteurisation and correct measurement. All these operations present challenges to maintain safety and quality, presenting the need for close monitoring during transportation. Hearts was also founded to support and facilitate milk bank research. As part of continuous service improvement, the HMF wished to amend the lack of research into DHM transportation. While there is only one recent article that address monitoring of DHM [14], a review of the literature has yielded no other previous study in this context of IoT use in DHM, especially during transportation of DHM. Therefore, the objective of the present case study is to assess the implementation of digital tools, namely Internet of Things (IoT) sensors and big data technologies, for DHM loss and waste reduction during transportation, as well as to evaluate the resulting economic and social impact. This is a significant research gap because there have been no research studies to date on how IoT technologies can support DHM loss during transportation.

The aim of this case study is to identify how technology can minimise the risk of DHM wastage during transportation and support HMBs by monitoring conditions that may increase the risk of spoilage, such as temperature and humidity, whilst optimising quality control. The REAMIT project team worked to improve logistics and produce world-first data on DHM transportation. The pilot test's aims were to develop systems to monitor temperature within insulated human milk transport bags, maintain transportation temperatures and reduce the cost of transportation by optimising logistical operations whilst achieving the capacity to support 500 DHM journeys per month. To achieve our research objectives, we have conducted a detailed search of the literature for the challenges involved in avoiding DHM wastage and related policies (Section 2). We describe various processes involved in the collection and delivery of DHM (Section 3), and then describe the specific service of the case company, the HMF (Section 4). Section 5 provides solutions to quality issues from the case study observation, and Section 6 concludes the article with suggestions, limitations and future research.

2. Background Study

2.1. Challenges of Producing and Maintaining Optimal Quality of Human Milk

In 2008, the WHO promoted the safe use of human milk from HMBs [15]. Human milk banks collect and store DHM that is later consumed by vulnerable neonates [10]. However, scaling up this lifesaving intervention has been challenging [16]. DHM therefore remains a relatively expensive nutritional alternative as a result of costs associated with donor screening, milk collection and handling, transportation, pasteurisation, measurement and storage processes to create a safe product [10]. The cost of 1 L of donor human milk in the UK has been estimated at 140 to 170 €, which exceeds the price of preterm formula ten times [10]. As human milk is an expensive and limited commodity, the policies and procedures related to its transportation, processing and storage should be optimised so that this resource is not wasted.

A Health Technology Assessment (HTA) report entitled 'Breastfeeding promotion for infants in neonatal units: a systematic review and economic analysis' was published in 2009 [17]. This report used systematic review methodology and health economic modelling to assess which interventions, including the availability of DHM, effectively promote the initiation and duration of breastfeeding in neonatal, special and intensive care settings. The authors noted that in the UK, DHM is neither widely nor readily available in the majority of units; this was reflected through modelling the use of DHM by availability, not need. They concluded that if mechanisms by which DHM is provided were improved, donor milk would become cost-effective compared with infant formula. This conclusion was based on a significant improvement in the operation of milk-banking HMBs, and suggested models included establishing a national donor milk HMB banking system similar to that for blood [18].

In order to meet the growing demand for DHM, there is a need to increase donations, which requires recruiting new volunteers and monitoring each phase of processing to avoid waste [19]. A study with 30 women performed by Muller et al. [20] identified the knowledge and practice of lactating mothers regarding human milk donation. The study examined the attitudes and motivations of 27 postpartum women; "excess milk" was the main reason for nine mothers to donate. Among those who did not donate, the reasons given were: "I did not seek to donate; little milk; difficulty milking". Muller et al. [20] interviewed 36 donors registered at a human milk bank in Brazil and showed that the reasons for human milk donation cited were the overproduction of milk and altruism. Mothers of older children expressed frustration that they did not know they could have donated after previous births, primarily as a result of a lack of information, lack of institutional support or misinformation from healthcare professionals [19].

With the increasing use of DHM, maintaining its quality, preserving the nutritional and immunologic constituents of the milk and ensuring optimal infection control are important challenges. HMBs receive and process milk from donors of different ages, economic, social, cultural and nutritional conditions [21] with carefully designed standards that minimise risk to the recipient infants while ensuring that women have the opportunity to become donors. These standards also apply to the collection, transportation and storage of the milk, as well as processing (pasteurisation) and analysing to select the appropriate milk that may include consideration of the colour, off-flavour, physicochemical and microbiological composition [19]. Thus, optimizing the quality control services of HMBs is crucial.

2.2. Policies and Operation of Human Milk Bank Services

In the UK, HMBs follow guidance issued by various bodies, including the National Institute for Health and Clinical Excellence (NICE). The NICE clinical guideline #93 for the operation of human milk banks aim to minimise the risk to recipients of DHM. Maximising safety comes at a cost, and recommendations were made to observe the best possible safety standards without exceeding opportunity costs acceptable to society. According to the NICE, "the implementation of the guidelines is the responsibility of local commissioners and/or providers, in their local context, in light of their duties to avoid unlawful discrimination and to have regard to promoting equality of opportunity".

3. Processes Involved in Human Milk Handling

Logistics from the donor (collection point) to the newborn babies (delivery point) involve several stages (Figure 1), including storage, pasteurisation and correct measurement. All of these operations are prone to the risk of quality. To ensure the quality of the milk in each stage, it is vital to have close monitoring of the logistics of the human milk journeys. Further explanation of each stage is given in the following sections.

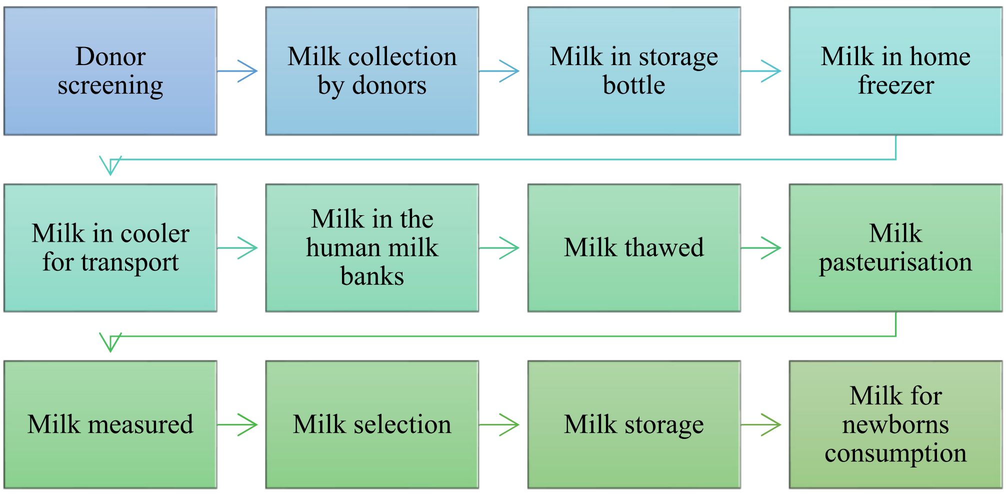


Figure 1. The human milk journeys. Adapted from Kim et al. [22].

3.1. Screening and Selecting Donors

In general, most human milk-banking countries commit to screening milk donors for the same blood-borne viruses as required by blood banks [23]. These tests meet international recommendations for human milk banking [24] and require tests of HIV, human T cell lymphotrophic virus (HTLV), hepatitis C, hepatitis B surface antigen, hepatitis B core antibody and syphilis antibody. Rationalization in some centres has led to dropping of screening for HTLV because this virus is destroyed by pasteurisation and freezing, and false positives are associated with influenza vaccination [23]. In Australia, women who have lived in the UK for 6 months or more between 1980 and 1996 are excluded as human milk donors because of the risk of transmission of variant Creutzfeld-Jakob Disease (vCJD) [23].

Donors who continue to donate for more than 3 months from the date of the initial blood test are required to repeat the blood test [25]. Milk collected during this period is stored until the results are known. Other reasons for excluding donors include an assessment of any medications or pharmacologically active products a donor may be taking that could be transferred to her breastmilk [23]. Questions relating to the use of prescription medication, smoking and alcohol consumption, etc., must be answered by the donors [24,25]. Much is known about the transference of medications to breastmilk, and exclusion of donors based on maternal drugs is rarely necessary but proceeds on a case-by-case basis [23,25,26].

According to the NICE [18], the stepped screening process detailed below should be followed when recruiting donors, and the potential donor should be advised that she is not eligible to donate milk if she:

- has previously tested positive for HIV 1 or 2, hepatitis B or C, HTLV type I or II or syphilis;
- is at an increased risk of vCJD;
- is using, or has recently used, recreational drugs;
- currently smokes or uses nicotine replacement therapy (NRT);
- regularly exceeds recommended alcohol levels for breastfeeding mothers (1 to 2 units, once or twice a week);
- exceeds more than three caffeinated drinks (150–200 ml) daily.

3.2. Milk Collection and Handling

Safe collection and handling practices are key to preventing bacterial contamination of human milk and avoid waste [27]. The Academy of Breastfeeding Medicine (ABM) created a protocol for collecting and handling human milk to minimize contamination or milk spoilage [28]. The guidelines advised women to wash their hands before expression with soap and water, or a waterless hand cleanser if their hands do not appear dirty. Unclean hands may transmit viruses and bacteria, some of which can cause illness [28]. In addition, some studies show that human milk containing fewer bacteria at the time of expression develops less bacterial growth during storage and has higher protein levels compared to milk that has an abundance of bacteria [29–31].

Milk expression can be achieved by hand or with a pump, and as long as the hand cleansing and cleaning of pump parts as per the pump manufacturer's instructions are appropriate, milk contamination with pumping versus hand expression does not present differences [28]. However, one study found that milk expressed at home [32] appears to have more bacterial contamination than milk expressed at the hospital; this is possibly related to equipment at home or transport, not to personal hygiene [33]. Several studies have been done to evaluate a range of available storage containers [22,34–37], and there is a mix of recommendations about containers to collect and store expressed milk [32]. According to Kim et al. [22], human milk collection containers should be sterile and standardized to minimize contamination risks, safeguard nutrient content and minimise maternal workload. DHM is stored in a variety of different bottle sizes typically ranging between 30- and 100-mL containers [10], depending on local HMB capability. Aronyk et al. [10] observed substantially less DHM is discarded when 50 mL bottles were used compared to 100 mL bottles in neonatal units.

Reyes-Foster et al. [27] studied the milk-handling practices of expressed human milk by donors. According to the authors, 78.9% of milk donors reported sanitizing pumping equipment and 82.3% washed their hands before handling expressed milk; 10% of milk donors reported participating in unsafe practices. Paredes et al. [19] observed a high human milk loss due to inadequate donor practices. The authors concluded that these were mainly as a result of total or partial non-compliance with the guidelines for biosecurity of human milk expression. It is noteworthy that the donors received sterile glass vials and hygiene training according to the national standards. However, this behaviour was persistent even with the prior and continued reception of guidelines. In the donors' homes, inadequate monitoring of freezer temperatures can cause microbiological multiplication and consequently increased contamination. In addition, home practice tends to differ from safety standards and most of the problems involving the quality of the human milk resulted from domestic collection and handling, with frequent contamination by elements of this environment [19].

Knowledge of appropriate human milk collection and handling is essential for breastfeeding success in these situations. According to many studies, human milk is generally kept in a frozen state at −20 °C, but it can be refrigerated (+4 °C) for at least 96 h for use at home [9,19,22,24,27,28], although NICE guidance is for all expressed milk to be frozen within 24 h of expression.

3.3. Transportation, Handling and Tracking

Transporting human milk from home to the milk bank or hospital should be standardised by maintaining cooled or frozen milk in an insulated container packed with ice or freezer gel packs [38]. The insulated container must be disinfected between each use, and the breastfeeding protocol also recommends avoiding using regular ice because it is warmer than frozen milk and will cause the milk to thaw [39].

The length of time that the milk stays frozen or chilled can vary according to the outside temperature and if donors follow the milk bank's instructions [39], but commonly, human milk can be stored safely while being transported in a cooler for up to 24 h with frozen gel packs. Additional frozen gel packs may be needed if containers are only partly filled because bottles filled partially with frozen milk will stay frozen longer than completely filled containers [39]. The opening of cooler bags should be limited because allowing milk to warm during transport will increase the risk of bacterial growth.

According to the NICE guideline, before pasteurisation, a sample from each batch of pooled DHM should be tested for microbial contamination, and if samples exceed a count of 10^5 cfu/mL for total viable microorganisms, 10^4 cfu/mL for Enterobacteriaceae or 10^4 cfu/mL for Staphylococcus aureus, then the milk should be discarded. DHM containers should be labelled clearly for identification. DHM should be supplied to hospitals or neonatal units that agree to comply with the tracking procedures for milk outlined by the milk bank.

3.4. Pasteurisation

Most human milk banks do not practice prepasteurisation testing because rigorous bacterial screening can result in approximately 30% of the milk being discarded [16]. This bacterial screening regime has shown that the bacterial content of donated milk varies greatly between donors and even between individual donations by the same donor. Discarding the milk prior to pasteurisation will outweigh the benefit of this screening test and can potentially increase the expenditure for human milk banks; for this reason, pasteurisation is commonly done prior to testing. International best practice requires that human milk be pasteurised (heated to 62.5 °C for 30 min) prior to being fed to newborns [24]. The efficacy of any pasteuriser is dependent on both the pasteurising temperature and hold time and the time taken to heat and subsequently cool the milk, which can vary between pasteurisers [24].

In most countries, human milk banks do not routinely pasteurise human milk. The risks of feeding contaminated human milk to very preterm newborns are unknown, as are the risks of feeding sterile, pasteurised human milk or formula on the development of the preterm immune system. A study compared raw and pasteurised human milk with substitute formulas and demonstrated that pasteurisation reduced the protective effects of human milk in about 14.3% for infections, but newborns fed with pasteurised human milk had lower infection rates (33.3%) than those fed with formula [40].

Alternative technologies that are currently being tested to prevent microorganism bioactivity while ensuring safety of donor milk include high-temperature short-time (HTST) treatment, high pressure processing (HPP), ultraviolet (UV) irradiation and ultrasonic processing [41]. Studies using ultrasonic processing of bovine milk and fruit juice suggested that this method may be potentially useful for pasteurisation and homogenisation of human milk because it can effectively eliminate various food-borne pathogens, including *L. monocytogenes*, *Salmonella spp*, *E. coli*, *S. aureus* and *B. subtilis* [42,43]. A real-time polymerase chain reaction method for the specific and rapid detection and quantification of bacteria and pathogens in human milk is also currently being developed. This will allow milk that is heavily contaminated or contains pathogens to be identified and discarded prior to pasteurisation [23].

Alternative approaches are used internationally to increase efficiency and reduce cost while maintaining acceptable safety. According to Simmer [23], in some countries, DHM is distributed raw or pasteurised to very preterm and term newborns based on the level of contamination and risk to the patient. For example, in Germany, either raw or pasteurised human milk with a number of bacteria < 10^3 cfu/mL is used for feeding newborns weighing less than 1500 g, whereas milk containing 10^4–10^5 cfu/mL is analysed for pathogens and pasteurised for feeding older babies [23], which appears to be a pragmatic approach to minimise the waste of donations. Most hospital policies stipulate that human milk containers can only be used to feed a single newborn and cannot be shared [10]. Although not acceptable in some jurisdictions, the implementation of policies which allow traced sharing of human milk bottles between a limited number of newborns may also mitigate the wastage of this resource [10].

3.5. Bacteriological Testing of Milk (Selection and Classification)

Human milk is not consistently bacteriologically examined after pasteurisation in all human milk banks, whilst bacterial count limits for rejecting milk vary between the banks according to the guidelines for each country [23]. These limits are required as pasteurisation may not be effective if milk is heavily contaminated [44]. In addition, although pasteurisation eliminates most organisms, the toxins produced by some bacteria may not necessarily be destroyed by heat [44]. Therefore, any bacterial growth is identified by standard microbiological techniques, and colony growth is also quantified [25].

Simmer [23] observed a human milk bank in Australia that had processed over 1400 batches of DHM since its establishment in 2006. According to the author, only 36 batches showed bacterial growth postpasteurisation. This growth usually comprised low colony counts of coagulase negative *staphylococcus*, but very occasionally high growth of *Bacillus cereus*, a known foodborne pathogen. Only five of the 36 batches showed bacteria growth greater than 10^5 cfu/mL. Although current evidence would suggest a low likelihood of bacteria that had been present in DHM prior to pasteurisation causing a clinical issue for a recipient of DHM, the extreme vulnerability of the recipients precludes their use, and these batches are discarded.

Paredes et al. [19] identified the causes of wastage in an HMB in Brazil during the selection and classification phases. Data of 383 donors were analysed, with a volume of 711.8 L human milk. According to the authors, the volume of human milk wasted due to dornic acidity tests, non-conforming off-flavour and the presence of dirt was equal to 64.3 L (9%). The dornic acidity method has been used to evaluate bacterial growth. Human milk has the sorption capacity of volatile substances, and the term off-flavour designates an unsuitable milk characteristic for consumption. The microbiological quality control (total coliform survey) after pasteurisation was responsible for a total of 31.6 L (4.4%) of human milk wasted.

Therefore, through continued actions, health education can reduce process losses and establish safe and reliable habits for the preservation and processing of DHM. Bacterial screening is a major area for further research to ensure the validity of HMB processes and efficiencies.

3.6. Storage of Milk in HMBs

Although guidelines for safe usage vary between networks, the milk in UK milk banks must generally be stored at −20 °C. If frozen, the milk can only be thawed once, and the remaining excess must be stored at 4 °C and used within 24 h [10].

Most recommendations for the optimal duration of milk storage have focused on bacterial colony counts as measurements of milk contamination. The lack of significant increases in bacterial colony counts is important and is indicative of an active host defence system in the milk [45]. Although the changes in bacterial counts are reassuring to the integrity of milk, it is important to know the major changes in macronutrients and immune factors, such as sIgA, lactoferrin, total fat and total protein, to further support the safety of refrigerator storage for 24 h.

Refrigerators for human milk storage must be able to maintain temperatures at 4 °C, and freezers must allow for temperatures at or below −20 °C for long-term storage [9]. Adequate space to store human milk while allowing for appropriate airflow is also important to ensure proper temperatures. A reliable method of temperature monitoring prevents loss and promotes safety [9]. Use of automated systems that alarm when temperatures exceed desired ranges may be beneficial. In addition, the location of refrigeration units in areas with limited access may help prevent tampering and waste, but is balanced by the need for temperatures to be monitored daily.

4. Methodology

In this research article, a case study approach was used to understand the role of technology in maintaining the quality of human milk. As part of the REAMIT project, the focus was on maintaining the quality of human milk when the milk is being transported by volunteers from homes to the milk bank. Accordingly, detailed descriptions of the technology demonstration of IoT sensors within the case organisation and records of the use of IoT sensors in the case of DHM storage and delivery are provided. Observation of the HMF's operations and trials are recorded for further analysis.

4.1. Background

The Human Milk Foundation (HMF) is a UK charity launched in 2018 to support human milk research and education and to develop nationally equitable human milk-banking services. The HMF provides DHM to hospital neonatal units for infants in neonatal care through the Hearts Milk Bank, which was initially established as a social enterprise community interest company to facilitate speed of establishment, and then merged into the HMF in 2019. Hearts Milk Bank also provides DHM and specialist lactation support to families where mothers are facing breastfeeding challenges or are unable to provide any of their own milk, and these services are free to families.

The annual capacity of the Hearts Milk Bank is 5,000 L, with donations transported via volunteer 'blood bikers' who deliver blood donations to UK hospitals outside of normal hours. This volunteer system is almost unique to the UK and Ireland. Although DHM is regulated as a food in the UK, transportation of DHM is outside the framework for the transportation of food. Some aspects of food regulation are very difficult to apply to human milk, particularly labelling. This is mostly due to every container of DHM having a different nutritional content. Therefore, this makes it impossible for the HMF to properly label each milk container with nutritional information, as required by food standards in the UK. More information about the HMF can be found in [13].

HMB models vary globally from a single human milk bank that may serve an entire country to smaller regional HMBs, or those that serve a single hospital. In the UK, HMBs are often situated within hospitals, funded by the hospital or local healthcare trust they are operating in. Hospitals reimburse HMBs for costs related to donor screening and DHM processing. It is important that the HMF ensure human milk donations are being used optimally; however, inevitably there is some milk wastage if donations fail the stringent microbiology tests before and after pasteurization. As well as the costs to the charity and reduced volume of anticipated available DHM, the negative impacts to donors for the lost time, effort and emotional investment are also important.

4.2. Hearts Milk Bank (HMB)

When donated milk arrives at Hearts Milk Bank (HMB), it is checked visually to ensure it is still frozen before being stored within the milk bank at −20 °C prior to screening and processing (microbiological assays, pasteurisation etc.). Once packed, the product is stored again at −20 °C until it is needed by a recipient and transported by volunteer courier to a hospital neonatal care unit or to a recipient's home.

4.3. Operational Conditions

Mothers are able to donate their milk to the HMF if they are breastfeeding, either from home or from a hospital, and have surplus milk. As with blood banking or tissue banking, donors all undergo prior health and serology screening. There are also strict guidelines for the storage and transportation of human milk that both the HMF and recipient hospitals must ensure are followed.

The HMF operates across England, Wales, Northern Ireland and Ireland, with donation and recipient locations ranging from a couple of miles to several hundred miles per journey. Therefore, transportation times can be up to 24 h long, so stable and robust transportation temperature is needed.

Figure 2 illustrates the DHM transportation pathway. DHM is collected either in the hospital or at home with the help of volunteers and transported to HMB using motorcycles or an electric car. Transportation is done in dedicated storage boxes with appropriate cool packs. After visual check, the milk is stored for processing and a sample is sent to the lab for screening. If the sample passes screening, it is packed and stored in HMB, ready for re-distribution to either hospitals or the homes of recipients.

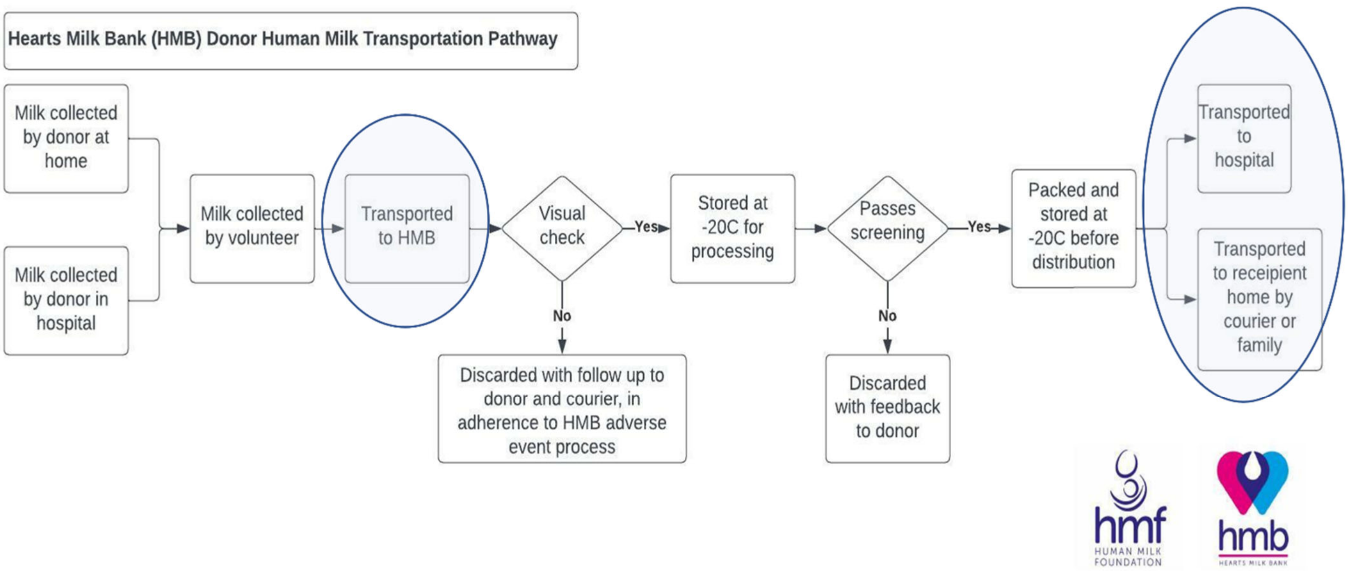


Figure 2. Hearts Milk Bank Donor Human Milk Transportation Pathway. The shaded areas in Figure 2 show when the milk is on transportation, which is the focus of the use of IoT sensors for monitoring temperature.

DHM is transported in frozen form within insulated containers as shown in Figure 2. Cool packs are used to maintain a temperature of −15 °C within the container, and there is no additional cooling operator. Several litres of DHM are transported at a time within the insulated containers on a motorcycle, with specialised insulated transport boxes able to transport up to 20 litres at a time.

At the HMF, the milk is heat-treated at 62.5 °C for 30 min and stored until tests confirm it is safe for consumption. Whilst the milk is being stored, the temperature is monitored either by the donor or by the hospital. In the milk bank, all freezers are monitored with temperature sensors that are linked with alarms that can send notifications to computers and emergency phone systems.

4.4. Problems

DHM needs to be transported safely to maintain its optimal quality; therefore, a key priority for the HMF is monitoring the temperature of the milk during transportation time. Prior to collaboration with the REAMIT project, the HMF was unable to accurately monitor the temperature during transportation. However, the charity also wanted to ensure that the milk remained in optimal conditions throughout the whole period from when milk is made available from the donor until the milk has been delivered to its recipient. Due to being unable to monitor the temperature and environmental conditions, the HMF was unsure if the milk was maintained at its optimal temperature during the transportation time. This is important as temperature and humidity are main factors of DHM wastage. The HMF discharge rate is equal to 7–8%; however, a weekly discard rate of up to 25% is not unusual in HMBs during the warmer summer months. The impact of heat waves and unstable climate may exacerbate difficulties in the transportation of DHM.

High temperatures and fluctuating levels of humidity during transportation impact quality of the human milk. However, the main factor underlying DHM wastage is microbiological contamination at the point of expression. As well as supporting donor education and providing sterile containers, HMB also uses other safeguards to minimise the risk of microbiological failure. Containers of donated milk are only opened within an ultra-microfilter Class 2 Biosafety Cabinet, and ultraviolet light is used in the biosafety cabinet to disinfect tools and containers used during processing. Equipment is then sterilised using an industrial dishwasher (Miele, Germany), which heats equipment to over 85 °C.

5. Adapting Internet of Things and Big Data Technologies to Monitor Temperature of Milk during Transportation for HMF—REAMIT Technology Demonstration

Recent literature has highlighted the growing applications of Internet of Things (IoT) and big data technologies in the food industry (e.g., [46–48] and in logistics [47]). However, an application in the context of human milk and its transportation is almost non-existent. In this section, we present the details of how we adapted existing IoT and big data technology for the HMF.

Having assessed the challenge at the HMF to monitor the temperature of the milk during the transportation stage, REAMIT proposed a series of sensors which seemed most suitable to address the challenge, i.e., Digital Matter Eagle Logger—GPS/Accel, T9602 T/RH. Twelve sensors monitored the temperature and humidity of the milk during transportation between the donor's house to the human milk bank, and from the human milk bank to the hospital or home of a vulnerable baby. At the beginning of 2021, the HMF had one human milk collection hub that is used to concentrate the donations in order to reduce transportation needs. Currently (end of 2022), the HMF has four hubs, and three are in the pipeline.

The sensors were installed in the insulated bags shown in Figure 3. One of the lessons learnt during sensor installation is the necessity to re-position the sensors inside the milk bag in order to record the data better. The sensors were sent on trips inside the transportation bags where they collected and transmitted the data to the cloud and the big data server. The procedure for using data from sensors for monitoring quality of donor human milk during transportation is shown in the schematic in Figure 4.

Figure 3. Insulated human milk transport bag used by the HMF to transport milk.

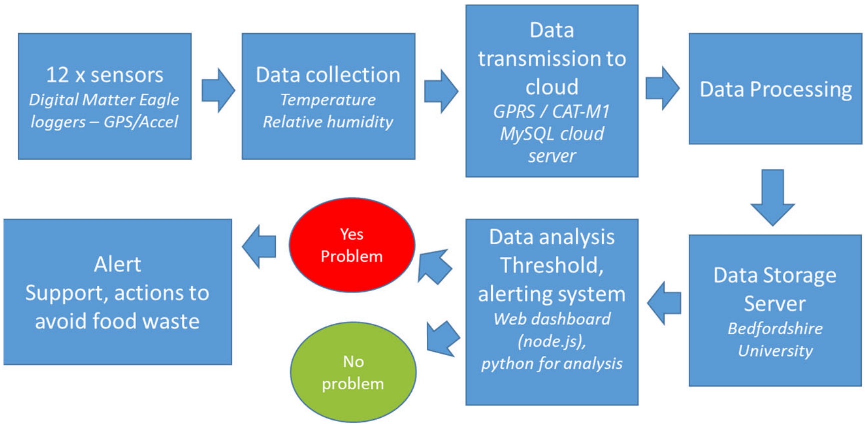


Figure 4. A schematic of using data from sensors for monitoring temperature in which human milk is transported.

As shown in Figure 4, the sensors installed in the human milk transport bags are Digital Matter Eagle loggers (Figure 5). The sensors have a GPS that generates data on the location of the milk and when the sensor is in motion. In this way, it creates an alerting system without human intervention.

Figure 5. Sensor placed inside the insulated human milk bag.

For each journey, the sensor installed within the insulated human milk transport bag monitors temperature and humidity conditions. Due to the nature of the transportation, the system has been designed as a standalone, battery-driven system. The temperature and humidity data from the sensors are collected every 30 min, whilst the GPS locator sends data every 2 min (and less frequent when the mode of delivery, bike or car, is stationary).

The data are collected in the cloud (the specially commissioned server for the REAMIT project) using GPRS/CAT-M1 technology. The server uses SQL technology for storing and retrieving data for access by a team of data analytics professionals. Data collected with sensors are uploaded to the REAMIT project cloud via an internet connection and administered by partners at the Whysor company, a Dutch-based REAMIT partner company, specialising in IoT sensors technology. Whysor created a dashboard to present data collected from all sensors installed at the HMF. The sensors are configured to record data every 5 min while in a trip, or every 12 h outside of a trip.

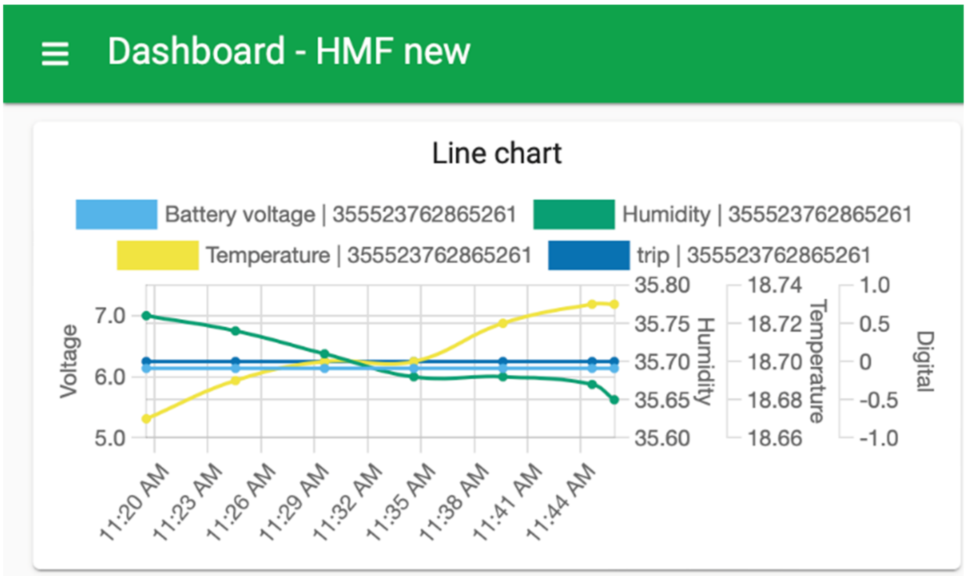
A special feature of the dashboard and the data analytics algorithms employed for analytics is that they have been designed to send alerts when the temperature of the milk is above the prespecified threshold instructed by the HMF and above −20 °C. The alerts are sent via email and as a smartphone message. These alerts are crucial in ensuring that the temperature of milk is kept at optimal levels during transportation. If the temperature is consistently within the allowed threshold throughout a journey, then it can be assumed that the quality of milk is maintained at optimal levels.

In order to prevent false alerts, the analytics algorithms have been designed to send alerts only when (i) there are three consecutive temperature values outside the threshold and (ii) when the binary sensors indicate that the sensors are being used during milk transportation and not when the bags are kept within the premises of the organisation.

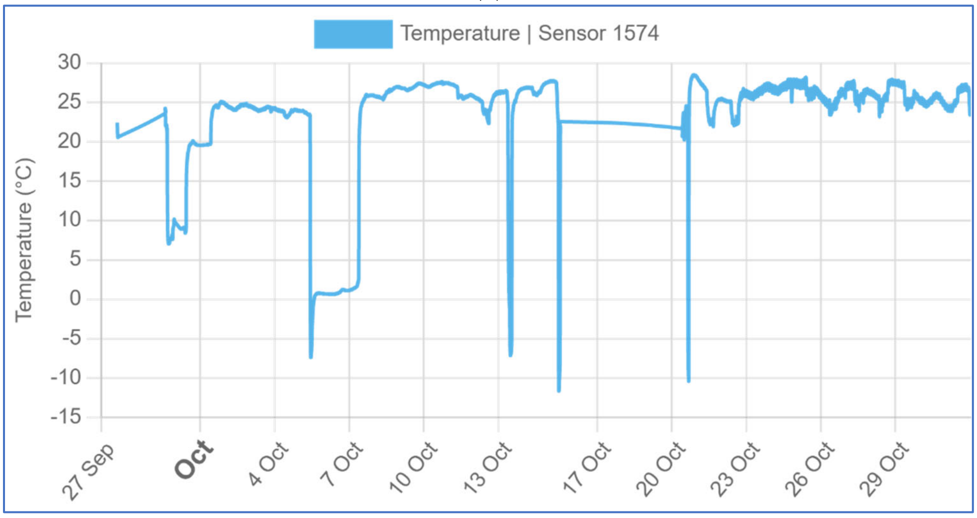
One of the challenges faced in this pilot test was to upload the data collected with sensors to the cloud, as it was the most energy-consuming part of the data collection process and lead to exhausting the batteries. Some ideas were explored, such as using rechargeable batteries (which was a challenge as it required certain voltages) and using other kinds of batteries, such as Altium. The possibility of using light (optical) sensors was also discussed, which would be able to pick up moments when the milk bag is opened and closed. The solution found to save battery energy was to disable sensor alarming functionalities when it was not necessary to send alerts, i.e., when the bags are not transporting milk.

Other, more sophisticated analytics on data from sensors were performed by a data analytics team. For example, the sophisticated statistical process control analysis was performed on the sensor data. Life cycle analysis (LCA) was also performed. LCA has been discussed in detail in another paper in this Special Issue [49]. Figure 6a shows a time-series plot of various measured parameters (such as battery level, temperature, humidity and trip details) found in the dashboard created for the HMF. Figure 6b shows a simple time-series plot of temperature for a specific set of dates. Data analytics included simple time-series plots, more sophisticated forecasting and other analytics models.

Figure 6b shows that the particular milk transportation bag was used only on specific dates: 05 October 2021, 07 October 2021, 13 October 2021, 15 October 2021 and 20 October 2021. There were some temperature changes on 29 and 30 September 2021, but it was due to the sensors being placed inside a fridge. The plot in Figure 6 has highlighted that the temperature data need to be linked to other related data to help comprehend the variations in temperature. Accordingly, it was decided to include a binary sensor in each bag to let the data analytics team know when the bag is opened and closed, which could help indicate that the bag is being used for transportation.



(**a**)



(**b**)

Figure 6. (**a**) Graphs showing the variations of temperature, humidity and other parameters from sensors placed in the milk transportation bags. (**b**) A simple time-series plot of temperature of milk in the milk transportation bags.

5.1. Strengths and Capabilities of IoT and Big Data Technologies

The technology demonstration explained in this article (see Figure 2) is a unique application of IoT and big data technologies to help the HMF increase quality of DHM and reduce waste. It fills a critical need for the charity in ensuring quality assurance when DHM is being transported. It is a bespoke system where IoT sensors not only track the temperature of the milk, but also follow the route of the volunteer. Sensor data are connected to the cloud, and the charity is able to see the temperature in real time. Automated big data algorithms help send timely alerts if the temperature fluctuates beyond acceptable levels to enable the charity to take appropriate corrective action rapidly. The collection of timeseries data from sensors provide further appropriate analytics options. For example, if there are multiple routes that the milk volunteers take, sensor data can be used to choose the most suitable route. Assessment of the rate of change of milk temperature over the distance travelled (or time) will help optimize the number of cool ice packs needed in the milk bags. These analyses form a strong scope for future research.

5.2. Saving Wastage of Milk and Improving Sustainability

While the HMF has sophisticated systems to maintain the quality of milk during storage in their premises, they found it challenging to ensure that milk is stored at the right temperature for maintaining the quality. In this case study, we have shown that modern Internet of Things sensors, cloud technology and big data analytics can help in monitoring the temperature to ensure the quality of milk and provide alerts if milk is not transported at the optimal temperature. By monitoring temperature continuously during transportation, this case study demonstrates that significant volumes of DHM could be saved and thus makes contributions towards sustainability.

1. Reduced wastage of milk: In theory, the continuous monitoring of milk temperature during transportation helps to detect quality issues on time. If the temperature of milk deviates from optimal levels, this deviation can be immediately detected with automated data analytics algorithms. Stakeholders can be immediately notified so that corrective actions are taken rapidly. However, our experience shows that milk is almost always stored at optimal temperature during transport. However, this continuous monitoring provides quality assurance as shown in the next point below.
2. Quality assurance of transported milk: Since the temperature of milk is monitored throughout transport, the organization obtains the reliability of assured quality of milk during transportation. Without this monitoring, while the organization made every effort to ensure optimal temperature, there was less reliability as temperature was not explicitly measured during the transportation of milk. It has to be noted that the organization has other means of quality assurance, for example by sending the milk to labs for testing before sending to hospitals. The monitoring of temperature of milk during transportation has added more levels of quality assurance.
3. Improved milk availability: Stocks of DHM are still relatively limited and therefore precious. By helping to minimize wastage of DHM, these technologies may increase availability, which could contribute to saving the lives of vulnerable babies through the avoidance of life-threatening complications.
4. Reduce costs: Continuous monitoring of temperature during milk transportation can help the organization reduce costs. For example, if the sensors indicate that milk is stored well below the lower threshold in which they have to be kept, it is an indication that too many resources are being used for cooling milk. This will help the organization to consider using lower energy for cooling—for example, by using fewer ice packs, which will reduce the cost of cooling.
5. Improve sustainability: The above points highlight how monitoring the temperature of milk using IoT technology can help not only save milk for organisations, but also support the social cause of improving milk availability to society. There are environmental benefits as well. For example, by helping to optimize cooling effort during milk transportation, energy can be saved, which translates to reduced carbon emissions. Thus, these technologies contribute to overall sustainability.

6. Conclusions and Future Research

Our research study is based on a real case study with observation of Hearts Milk Bank and REAMIT technology demonstrations. It is clearly evident that IoT sensors can support quality in maintaining cold supply chains of DHM. Dr. Natalie Shenker from the HMF (one of the authors) made the following statement on the benefit of REAMIT technology support:

> *"The REAMIT team have been fantastic! They've provided everything from proof of concept to the innovative sensors that we're using, that not only track temperature but are able to track humidity, acceleration, they can tell when the boxes will be actively moving—so we can really understand where the milk is, what conditions the milk is transported in and when it's arrived".*

DHM needs a high level of quality control which is possible with the support of smart technologies. IoT technology supports the human milk supply chain in five different aspects, namely in waste reduction, quality assurance, availability improvement, reduced cost and sustainability improvement. Our case study research proved that technological support is one of the easy ways to reduce waste and maintain sustainability. It was also realised by the case company in one of the interviews with the company personnel:

> *"The REAMIT project is a fantastic initiative, and they approached us about a year ago to see if we could work together to look at the cold chain technology and remote temperature sensing.*
>
> *One of the big question marks that we have about our cold chain is how well the milk is maintained at temperature, while it's being transported from donor's houses or from hospitals into the milk bank, and then again from the milk bank into the hospitals or recipient's families. It's really critical that we address that quickly and REAMIT is helping us to do that".*

Human milk requires a high level of safety and quality assurance. Although this human milk is classified as food, this requires very unique regulatory control that will not follow food transportation regulations. Future work on this topic can focus on regulatory requirements of the human milk.

While this is the first work in the context of using IoT sensors for monitoring quality of DHM during transportation, we faced some challenges when we implemented the technology. For example, there were issues with returning the sensors as volunteers chose to avoid coming to HMB for both onward and return journeys. Some volunteers chose to go to the pickup location directly from their homes. In this case, they were not able to pick up the sensors from the premises of HMB. Similarly, when a volunteer picked up milk from HMB for delivery to hospitals or the homes of recipients, they normally did not come back to HMB to return the sensors. This challenge sometimes affected the continued use of these sensors. Another limitation of the case study is the need to change the sensors' batteries. Changing batteries usually took some additional time, especially when the number of sensors was high.

As the world is going towards achieving sustainability in all possible ways, it is imperative to businesses to take the right initiatives and actions. Our study has considered one case organisation and tried to establish the use of IoT sensors in the DHM supply chain. This can be extended to other supply chains of rare and precious clinical resources, including blood and human organs, to avoid wastage and ensure total quality in supply chains.

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Article

Real-Time Anomaly Detection in Cold Chain Transportation Using IoT Technology

James Gillespie [1,*], Tamíris Pacheco da Costa [2], Xavier Cama-Moncunill [2], Trevor Cadden [3], Joan Condell [1], Tom Cowderoy [3], Elaine Ramsey [4], Fionnuala Murphy [2], Marco Kull [5], Robert Gallagher [6] and Ramakrishnan Ramanathan [7]

1 School of Computing, Engineering and Intelligent Systems, Ulster University, Londonderry BT48 7JL, Northern Ireland, UK
2 School of Biosystems & Food Engineering, University College Dublin, D04 V1W8 Dublin, Ireland
3 Department of Management, Leadership & Marketing, Ulster University, Belfast BT15 1ED, Northern Ireland, UK
4 Department of Global Business and Enterprise, Ulster University, Londonderry BT48 7JL, Northern Ireland, UK
5 Whysor B.V., 5944 ND Arcen, The Netherlands
6 Musgrave Northern Ireland, Belfast BT3 9HJ, Northern Ireland, UK
7 Essex Business School, University of Essex, Southend-on-Sea, Essex SS1 1LW, UK
* Correspondence: j.gillespie1@ulster.ac.uk

Abstract: There are approximately 88 million tonnes of food waste generated annually in the EU alone. Food spoilage during distribution accounts for some of this waste. To minimise this spoilage, it is of utmost importance to maintain the cold chain during the transportation of perishable foods such as meats, fruits, and vegetables. However, these products are often unfortunately wasted in large quantities when unpredictable failures occur in the refrigeration units of transport vehicles. This work proposes a real-time IoT anomaly detection system to detect equipment failures and provide decision support options to warehouse staff and delivery drivers, thus reducing potential food wastage. We developed a bespoke Internet of Things (IoT) solution for real-time product monitoring and alerting during cold chain transportation, which is based on the Digital Matter Eagle cellular data logger and two temperature probes. A visual dashboard was developed to allow logistics staff to perform monitoring, and business-defined temperature thresholds were used to develop a text and email decision support system, notifying relevant staff members if anomalies were detected. The IoT anomaly detection system was deployed with Musgrave Marketplace, Ireland's largest grocery distributor, in three of their delivery vans operating in the greater Belfast area. Results show that the LTE-M cellular IoT system is power efficient and avoids sending false alerts due to the novel alerting system which was developed based on trip detection.

Keywords: Internet of Things; IoT; food waste; cold chain; remote monitoring; sensor technology

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1. Introduction

Food safety is no longer a national problem but one of the major issues affecting humanity on a global scale [1]. Recent estimates indicate that 20% of food produced in the E.U. is lost, representing 88 million tonnes of food wasted annually, at the cost of almost €143 billion [2]. Additionally, food waste significantly impacts the environment, contributing to around 6% of all greenhouse gas (GHG) emissions in the EU and imposing an unnecessary burden on scarce natural resources, such as water and land use [3]. Reducing food waste has vast potential to save resources required to produce food, preserve food for human consumption, help farmers, companies and consumers to save money, and reduce the environmental impact of food production and consumption [4,5]. Food waste reduction and the need to adopt a more sustainable production and consumption model are priority areas in the European Green Deal and Farm to Fork plan due to their significant environmental and economic implications [6]. As part of this new strategy, the EU will intensify its action to prevent food waste along the whole food supply chain [6].

To maintain good product quality throughout the food supply chain, it is crucial to ensure that the food is handled under the proper environmental conditions [6,7]. In contrast to traditional supply chain management, the food in cold chains, such as chilled and frozen food, often have shorter shelf lives and are more sensitive to their surrounding environmental conditions, including temperature, humidity, and light intensity [8]. Thus, maintaining the required environmental conditions requires specialised refrigeration systems along the entire cold chain. Depending on the food being handled, the ambient temperature might range from −25 °C to +10 °C in the cold chain [9,10]. These temperature conditions reduce the development of microorganisms (pathogens and spoilage flora), as well as the rates at which changes occur in perishable foods, such as ripening rates, browning reactions or water losses [11,12].

Specific attention should be made to potential risks that might directly impact product quality and operational efficiency while handling food in an environment with such a low temperature [7]. Product quality risk is often defined as the degree to which a product falls short of consumers' expectations, resulting from product degradation and contamination across the cold chain [7]. Customer acceptability is heavily impacted by product quality degradation, which should be seriously regulated throughout the cold chain; otherwise, the product quality may fall below the acceptable level, resulting in waste and spoilage issues [13]. Companies may suffer losses if any potential anomalies emerge along the cold chain, which can compromise not only the product quality but also consumer health [14,15]. These anomalies can be caused by various factors, including refrigeration system failures, incorrect temperature settings in refrigeration systems, and very irregular temperature distribution owing to unequal air distribution or exposure to outside air during delivery loading and unloading [16,17]. The circumstances of transportation and storage play a significant role in the safety and quality of perishable food [18,19]. Derens et al. [20] found that the average temperature of food products during transportation is around 12% higher than recommended. A temperature break of 2 h during the transportation of perishable food may result in shelf-life decay by 10 to 40% [21], and the loss of products can reach as much as 35% [22]. Hence, the incidence of temperature anomalies can significantly influence the quality of highly perishable products [21]. In conventional cold chain management systems, vehicles and warehouses are often equipped with thermometers and humidity sensors [23,24]. However, this approach cannot dynamically communicate the information with remote users and can only display and record environmental information locally [25]. Additionally, it cannot determine the environmental conditions during vehicle switching, temporary storage, or truck loading, among other situations [25]. Typically, it also does not monitor the microcosmic environment in the boxes holding perishable food: only the macrocosmic environment in the warehouse or vehicles [25]. As a result, such systems cannot deliver continuous and real-time environmental information on perishable food.

In this sense, real-time environmental monitoring and control are critical for the safety and quality of perishable food and for tracking and evaluating the levels of risk throughout the cold chain [19,26,27]. In recent years, Internet of Things (IoT) technologies have been increasingly applied in the food industry due to their promising potential for more efficient monitoring in real time [28–30]. The IoT environment enables smart devices equipped with wireless communication technologies, sensors and actuators to connect to the internet and share their data in real time [31,32]. In the cold chain, IoT sensing technologies enable the automatic tracking and tracing of food items and surrounding conditions, resulting in transparent cold chain management [7,33]. In addition, food quality deterioration can be monitored in a real-time manner. Because of the progress of microelectronics technology, the cost and power consumption of IoT sensors have dropped substantially during the past few years [34–36]. With appropriate configuration, it may be set up to monitor various environmental conditions connected to food safety and quality, including temperature, humidity, light, vibration, carbon dioxide, ethylene, and others [25,37,38].

The main benefit of using these technologies is the ability to provide operators with automatic alerts to take corrective actions on time and prevent food quality deterioration [21,39]. In addition, IoT technology also enables supply chains to employ dynamic virtualisations in operational management procedures, which helps food organisations deal with perishable food products, unpredictable supply fluctuations, and strict food safety and sustainability requirements [40]. On the other hand, without real-time traceability systems, it is difficult to ensure that the food items are moved and maintained in stable specified environmental conditions along the cold chain [41]. Recent research discussed the development of cold chain monitoring systems using an online-decision-support system based on IoT technologies for fruits, vegetables, meat and fishery products [42–47]. The proposed systems monitor environmental conditions in real time and provide alerts on whether the temperature, humidity, or other factors exceed the safety limit. The combination of monitoring and decision-making support systems also showed promising results in reducing transportation losses. Furthermore, by installing the monitoring system, losses due to quality degradation were decreased, enhancing the overall performance of the food supply chain. The studies also showed that the product categories in the cold chain in which these technologies can be applied are varied [42–47].

Although real-time monitoring technologies on the cold chain will become more common in the coming years, several questions are raised by the imminent introduction of these new data monitoring sources, such as the placement of the sensors to take into account the entire load in the refrigeration equipment, the criteria for alert definition, and the methods for identifying and describing temperature abnormalities [21]. Regarding placement, numerous studies indicate that the temperature inside the refrigerated equipment is heterogeneous [11], and the current temperature control practice is complex because temperature measurements taken at one location may not represent what happens in the entire load. Additionally, only the ambient temperature is often monitored, while the product temperature may fluctuate, particularly in dynamic systems such as the cold chain [21]. The criteria for determining the alerts must also be well specified; a too lenient definition may result in undetected alerts and lead to food waste [21]. Conversely, too stringent criteria may result in false alerts and lead to food waste and high logistic costs [21]. Therefore, to create an effective alert system that reduces food waste, the total number of undetected and false alerts must be minimised [48]. Regarding the methods, to implement an efficient approach to detect temperature anomalies, a robust solution regarding the methodology used to determine the product temperature and the temperature distribution must be developed [49].

To our knowledge, there is still a lack of knowledge of potential anomalies, their characteristics such as occurrence, break level (gap between recommended and actual temperature) and their duration, especially for temperature anomalies caused by products remaining at low temperatures during deliveries. Hence, better characterising the temperature profile throughout the cold food chain is required to estimate and avoid food quality deterioration accurately.

In this context, this study proposes a real-time monitoring system that uses Internet of Things technologies to gather data on the environmental conditions (temperature and humidity) of perishable food during transportation. The real-time monitoring system comprises temperature/humidity sensors, a cellular logger (which both acts as a sensor recording device and a gateway), a Big Data server, a web dashboard for monitoring, and an intelligent anomaly alerting system. Accelerometer data and GPS coordinates are used to indicate trip detection, which is utilised for both smart alerting and to increase the battery lifespan. The proposed system was applied in delivery vehicles for a Northern Irish food wholesaler. Integrating these technologies should ensure the quality and safety of the food products under analysis throughout the cold supply chain.

2. Literature Review

2.1. Temperature Thresholds in Cold Chain Transportation

Temperature abuse in the cold chain can compromise food safety and quality. Therefore, to ensure high-quality food and prevent spoilage, transportation systems need to keep temperatures within close proximity to their safe, recommended refrigeration value [50]. In general terms, refrigerated food can be divided into four categories as to storage temperature: frozen, at −18 °C or below; cold-chilled, between 0 °C and 1 °C; medium-chilled, at 5 °C; and exotic-chilled, between 10 °C and 15 °C [51].

Chilled food, understood as any food product stored and kept at a temperature below that of ambient temperature, but above one where its water content will not start to freeze, is often preferred as a preservation method as it does not alter significantly quality characteristics such as texture, appearance and taste. Medium-chilled foods (5 °C), the type used in the present work, may include minced meat, processed fish, prepacked meat, ready-to-eat foods [52], cooked products, dairy products [53], and bakery products, among others [51].

Likewise, for frozen food, the integrity of the product, its packaging, and its temperature along the cold chain are all crucial quality factors. No other procedure can retain the quality attributes and properties of the original fresh food for such a long time as can contemporary freezing techniques and an uninterrupted chain of low-temperature storage and distribution. Due to the wide array of different foodstuffs each with their own physical and chemical composition, optimal temperatures for each type of frozen food product can vary and may be stored at temperatures more suited to their individual requirements (e.g., ice cream, dairy products, raw ingredients). While a maximum temperature of −12 °C is usually accepted as being acceptable practice for other frozen items, −18 °C is the standard (subject to adequate operational tolerances) for quick-frozen meals and legal requirement in the European Union (EC) and Great Britain [54]. It is worth noticing, however, that no frozen food poses a risk of microbiological development until the temperature is permitted to rise beyond −12 °C for an extended length of time [54]. In any case, transportation systems in the food supply chains must maintain the temperature of the food within close limits. The reasons for this are not only to ensure the safety of the food, as temperatures higher than −12 °C can pose a threat in terms of microbial growth, but also to guarantee that food retains its quality attributes, and maximum shelf-life.

2.2. Iot Monitoring Systems

In recent years, various IoT sensor systems have been developed and deployed to monitor the environmental parameters of perishable food and detect anomalies in real time. Table 1 presents some examples of systems proposed in the literature.

Table 1. Real-time food quality monitoring systems found in the literature.

Authors	Year	Product	Parameters Monitored	Communication	Real-Time Monitoring App	Alerting System	Trip Detection
Wang et al. [55]	2010	Perishable products	T, RH, V, GPS	RFID, GPRS	✓	✓	✗
Haflioason et al. [48]	2012	Cod	T	WSN	✗	✗	✗
Chen et al. [56]	2014	Perishable products	T	2G	✗	✓	✗
Aung et al. [19]	2014	Banana	T, RH, CO_2	ZigBee	✗	✗	✗
Thakur et al. [57]	2015	Chilled lamb products	T	GSM/GPRS	✓	✗	✗
Xiao et al. [58]	2016	Fish (tilapia)	T	ZigBee	✓	✗	✗
Jedermann et al. [59]	2017	Banana	T, RH, CO_2	GSM cellular	✗	✗	✗
Xiao et al. [60]	2017	Table grapes	T, RH, VOC	GPRS	✗	✗	✗
Alfian et al. [61]	2017	Kimchi	T, RH, GPS	WiFi	✓	✗	✗
Musa et al. [62]	2017	Blackberry	T, RH, CO_2, LI	RFID and WiFi	✗	✓	✗
Tsang et al. [7]	2018	Meat and seafood	T, RH, LI	Bluetooth, Wi-Fi and 3G/4G	✓	✓	✗
Wang et al. [45]	2018	Holly	T, RH, CO_2, C_2H_4	4G	✓	✓	✗
Wang et al. [63]	2018	Peach	T, RH, O_2, CO_2, C_2H_4	4G	✗	✓	✗
Morillo et al. [64]	2018	Meals	T	WSN, Bluetooth and 3G/4G	✗	✗	✗
Tsang et al. [47]	2018	Fruit	T, RH	GPRS (3G, 4G, LTE)	✓	✗	✗
Mondal et al. [65]	2019	Perishable products	T	RFID	✗	✗	✗

Table 1. *Cont.*

Authors	Year	Product	Parameters Monitored	Communication	Real-Time Monitoring App	Alerting System	Trip Detection
Feng et al. [43]	2020	Shellfish	T, RH, O_2, CO_2	Zigbee and GPRS	✓	✗	✗
Zhang et al. [66]	2020	Sweet Cherry	T, RH, O_2, CO_2, C_2H_4	USB	✗	✗	✗
Torres-Sanchez et al. [67]	2020	Lettuces	T	WiFi and GPRS	✗	✗	✗
Urbano et al. [68]	2020	Pumpkin and oranges	T, RH	RFID, 3G/4G, WiFi, LoRa, NB-IoT	✗	✗	✗
Markovic et al. [69]	2020	Meat	T	Bluetooth	✓	✗	✗
Afreen et al. [70]	2021	Fruit and Vegetables	T, RH, LI, VOC	WiFi	✓	✓	✗
Zhu et al. [71]	2021	Garlic scape	T, RH, VOC, V	4G	✓	✗	✗
Li. [72]	2021	Fruits and vegetables	T, GPS	5G	✗	✗	✗
Gillespie et al.	2023	Perishable and frozen products	T, RH, GPS	LTE-M	✓	✓	✓

T, Temperature; H, Humidity; V, Velocity; GPS, Global Positioning System; RH, Relative Humidity; CO_2, Carbon Dioxide; VOC, Volatile Organic Compound; LI, Light; O_2, Oxygen; C_2H_4, Ethylene.

As shown in Table 1, there are a significant number of the studies which present a real-time monitoring interface to visualise the live data of environmental parameters in cold chain transportation. Some articles such as that of Afreen et al. [70] used a smartphone-based approach (Android App) for data visualisation, which while effective limits users of the software to a mobile device with limited screen size. Others such as Xiao et al. offered desktop-based visualisation by developing a Windows application for real-time monitoring [58]. The drawback of these solutions, however, is firstly the limiting convenience factor of being restricted to a personal computer to access the data, and secondly, the operating system compatibility restrictions imposed by Windows-based applications. The third type of interface observed in the literature is employed by authors such as Alfian et al. [61], who developed a web dashboard allowing for monitoring on multiple devices.

However, the existing studies remain limited in presenting a mechanism to alert the personnel in the case of broaching safety thresholds of environmental parameters. Only a few studies mentioned the presence of early warning systems.

The first noted occurrence of real-time parameter monitoring with an alerting system implemented is found in the work of Wang et al. [55]. In this research, the authors propose a rule-based system for alerting during the transportation of perishable products in containers. Nonetheless, the notification system in this work is limited to an alert within a bespoke Windows application. Chen et al. [56] proposed a temperature monitoring and alerting system for perishable goods based on Radio Field Identification (RFID) technology. In this work, the alerts were only delivered to either the RFID device or the mobile phone once the RFID tag on the product had been scanned. Afreen et al. [70] evaluated the implementation of IoT technologies to monitor fruit and vegetables according to different environmental parameters (temperature, relative humidity, light intensity, and concentration of gas). The system implemented in this study sends a notification to personnel for timely necessary action. Despite this, the prototype system is in a fixed cold store, not moving transport. Tsang et al. [7] monitored the temperature, humidity and light intensity of meat and seafood products. The authors discussed implementing an alert system based on thresholds in their study, yet no technical information was presented on how alerting criteria was configured or how it was implemented, leaving it unclear if the proposed alerting system was device, application, or platform specific. Musa et al. [62] discussed a theoretical framework for alerting based on a fog-computing architecture to handle the computation; however, the framework was not implemented in the research. Wang et al. [45,63] studied the transport conditions of holly and peach. According to the authors, the system provides an early warning for the need to take effective proactive measures and prevent unexpected quality loss, improve the quality control and transparency of fruit export chain. However, no further details as to how it was configured were provided.

The novelty of this work is a trip detection system, of which one of its main benefits is to increase the sensors' battery lifespan. However, some studies have made efforts to ensure the battery consumption of the IoT system is kept to a minimum. Torres-Sanchez et al. [67] discussed the development of a "time-synchronizing" algorithm to reduce the slot time that the slave nodes are connected to the Wi-Fi network. However, this conceptual framework was not applied to real-world problems. Markovic et al. [69] also discussed the frequency of parameter recordings in their study to optimise battery life. According to the authors, if a constraint encoding a maximum allowed temperature for a specific delivery stage has been exceeded, the device will enter "alert" mode and the measurement frequency is increased. If four consecutive readings exceed this threshold, an event is logged to mark the current delivery stage as non-compliant, and the readings demonstrating this non-compliance are also stored.

The battery-saving benefits trip detection delivers is due to the reduced monitoring recordings while the food products are not in a trip, which in turn extends the battery lifespan and reduces their respective environmental impacts. However, detecting vehicle motion also allows for the production of intelligent alerts. The proposed system sends an automatic notification to personnel if the thresholds of monitored parameters are abused, which contributes to taking timely necessary action to mitigate the loss of perishable products. In addition, the proposed system provides support of a scalable web dashboard for remote monitoring and personnel can check the food transport conditions on any device, at anytime, from anywhere.

3. Materials and Methods

In order to minimise the loss of perishable food products during transportation, a Real-Time Anomaly Detection (RTAD) system is proposed to automatically monitor real-time environmental parameters, such as temperature and relative humidity. Additionally, this paper aims to demonstrate that a wireless network system based on LTE-M communication can operate properly under the conditions of flexibility, signal loss resistance and power autonomy enough to be used in the cold supply chain. The designed system should be able to communicate in real time the measured variables with a power consumption capable of providing maximum battery autonomy. In this sense, a trip detection algorithm was also created to reduce the power consumption of the IoT devices under analysis.

The architecture of the RTAD system follows the standard 4-layer approach often employed by IoT systems. These are (1) the perception layer, (2) the network layer, (3) the processing layer, and (4) the application layer.

1. The perception layer, sometimes referred to as the sensing or data acquisition layer, is responsible for collecting data from the environment based on the sensor technologies employed in the sensor setup.

2. The network layer, sometimes called the communication layer, is responsible for receiving the obtained data and transferring it to the cloud storage service via a gateway. The gateway connects to the network layer using internet connection.

3. The processing layer, sometimes called the storage and control layer, consists of data storage and analytics. This layer is responsible for the retrieval of the data from the network layer, transforming it, and storing it accordingly. Additionally, this layer handles the processing of the data for alerting and intelligent analytics.

4. The application layer provides a front end in the form of an online dashboard to allow viewing of the data in real time. The application layer also consists of an alerting system, which operates as an SMS/email service to the user's mobile phone. The final component of the application layer is business reports which are prepared by the analytics team to give further insights into the recorded data.

Figure 1 provides a visualisation of the architecture employed for the IoT cold chain anomaly alerting system based on these 4 layers. The following sections provide more detail as to the components in each layer.

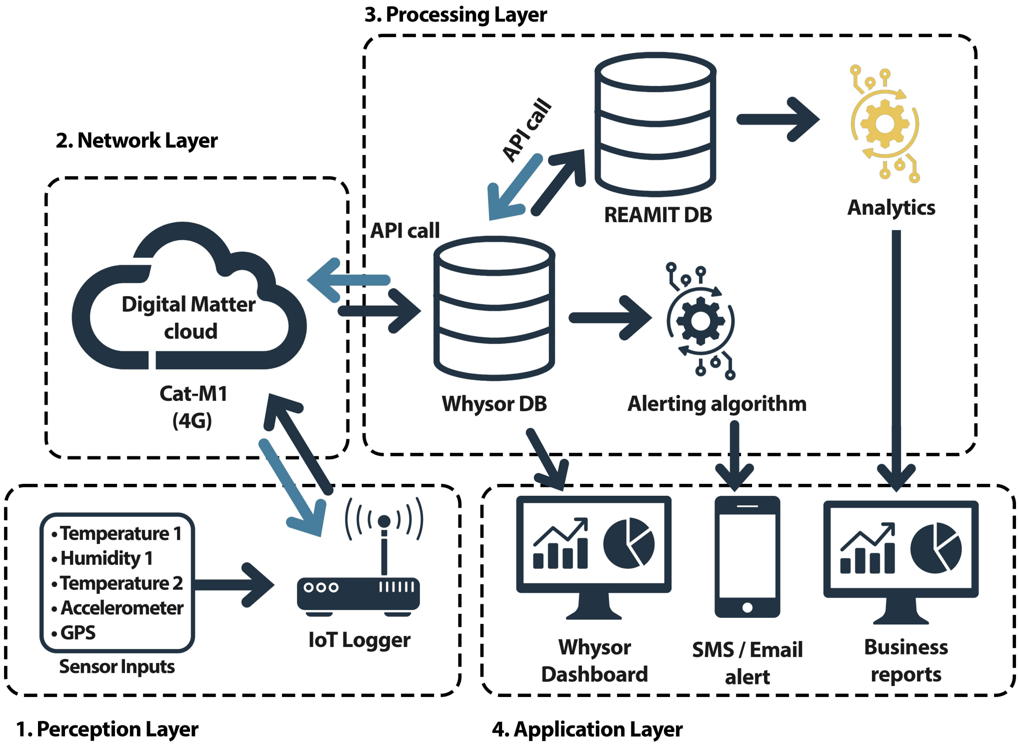


Figure 1. Architecture of proposed real-time anomaly detection system.

3.1. The Network Layer: Communication Protocol

A network down approach to architecture design was adopted when designing the IoT anomaly detection system, meaning the first area of the system considered and defined was the network layer protocol. This design approach was applied, as the chosen communication protocol would influence the rest of the sensor setup that could be deployed. The solution would require long-range transmission to connect the sensors to the cloud while the vehicles were in transport, while having low energy consumption would be required to ensure battery maintenance was kept to a minimum. Seminal works in the field focus on the low-energy aspect of the IoT requirement and propose technologies such as ZigBee and Bluetooth BLE for their IoT solutions [73,74]; however, these are based on short-range radio transmission and thus require a separate gateway device to interface with the world wide web. Solutions to combat the transmission range have been developed based on traditional cellular communication technologies (e.g., GPRS, 3G) [45,63]; however, these systems are very power intensive and thus inappropriate for long-term commercial use, where low maintenance is a driver toward technology acceptance.

Recently, however, a wireless communication technology called low-power wide area network (LPWAN) has emerged in response to the demands of Internet of Things applications. As the name suggests, this network operates on low power, has long range, and possesses affordable communication qualities. Sub-GHz unlicensed ISM bands (e.g., 868 MHz in Europe and 915 MHz in the U.S.) are used to operate LPWAN. In urban areas, the network allows for long-distance communication of 1–5 km, while in rural areas, it has a range of 10–40 km [75]. It is also very energy-efficient, with a typical end node (i.e., sensor) battery life of more than 10 years [76]. Because of this, the LPWAN communication protocol is gaining significant traction in both the industrial and research areas. While there are various implementations of LPWAN, the top emerging technologies at the moment are Sigfox, LoRa, NB-IoT, and LTE-M. As discussed, these technologies overcome the high-power consumption of conventional cellular networks and the range limitation of short-range networks while still providing an excellent radio penetration, which allows them to establish connection with objects located in intolerant or severe environments [77].

Sigfox is a wireless company and network operator that launched the first LPWAN technology in the IoT domain in 2009, and it has enjoyed popularity since. The physical layer of Sigfox is characterised by using binary phase-shift keying (BPSK) modulation, an ultra-narrow bandwith of 100 Hz and broadcasting on unlicensed ISM bands (e.g., 868 or 902 MHz). Its main advantages include a suitable range of 10 km in urban areas and up to 40 km in rural environments, low power consumption, high receiver sensitivity, and low-cost antenna design. However, its maximum throughput is 100 bps.

Another key, energy efficient and popular LPWAN technology that emerged in recent years is LoRa (from "long range"). Likewise, LoRa also uses unlicensed ISM bands (e.g., 868 or 915 MHz), although the modulation relies on chirp spread spectrum (CSS) and the bandwidths are 250 kHz and 125 kHz. It was first developed by in 2009, and in 2015, it was standardised by LoRa-Alliance. LoRa has established itself as a world leader for IoT communication and as such has been rolled out in 42 countries to date. Of these, however, only a select few have countrywide coverage (for example, the Netherlands and France [78]).

When considering the former technologies as candidates for the IoT solution proposed, one of the limitations encountered was the need for a broad network coverage suitable for the validation stage of the system: transport vehicles on the move delivering products in and around urban areas in northern Ireland. That is, the solution employed should not rely on a piece of hardware, or gateway, that provided network coverage in a limited area around its deployment location but rather a national-wide network coverage. Unfortunately, neither Sigfox or LoRa have the required national-wide coverage and thus would not be appropriate for the communication stack for the IoT solution being designed. Instead, a cellular telecommunication-based protocol would be required.

The other two popular LPWAN options that were considered were the Narrowband Internet of Things (NB-IoT) and Long-Term Evolution Machine (LTE-M). NB-IoT is part of the 3rd generation partnership project (3GPP) LTE specifications and shares several technical components with LTE. It can coexist with GSM and LTE under licensed frequency bands. Its main advantages are low power consumption, extended coverage and deep penetration [79]. The LTE-M network is derived from the 3GPP 4G LTE standard. Likewise, it also offers a low power consumption, long range and deep penetration. In fact, both NB-IoT and LTE-M share considerable similarities, with their main difference residing in the operational bands they use. These technologies were considered suitable candidates for the validation stage of the system as they were both available in northern Ireland. While both protocols offer a high degree of compatibility with standard 4G LTE and 5G networks, LTE-M was finally chosen as the communication protocol as it offered the added advantages of a range of bandwidth, latency, and mobility [80].

3.2. The Perception Layer

3.2.1. Iot Logger

With the requirement of LTE-M communication established, the Eagle datalogger (Digital Matter, South Africa) was selected as the platform for the development of the REAMIT solution. The logger is an IP67 rated rugged cellular IoT device, supporting a range of inputs for various IoT applications. The Eagle runs on either 4 $\times$ C Alkaline or Lithium Thionyl Chloride (LTC) batteries, or it can be wired to permanent power (6–16 V DC). It contains I2C, SDI-12 and RS-485 interfaces as well as 2 $\times$ analogue inputs, 3 $\times$ digital inputs, 2 $\times$ switched ground inputs, and 2 $\times$ 4–20 mA inputs, thus supporting a vast array of sensors to connect to the device. Additionally, it has an onboard GPS module and an accelerometer for geofencing and movement detection, and it is equipped with a SIM card allowing the device to run on the IoT low power LTE-M (CAT-M1) network [80]. The Eagle offers third-party cloud integration via an HTTPS webhook allowing for the convenient retrieval of recorded data for visualisation and analytics.

3.2.2. Sensors

A limitation of the Eagle's architecture was that I2C devices produced by third-party manufacturers could not be configured with custom addresses, and thus, the I2C communication bus only supported one sensor. For this, the highly accurate and robust T9602 Temperature/Relative Humidity (T/RH; ±2% RH, ±0.5 °C, 0.01 °C resolution) I2C sensor (Amphenol, Wallingford, CT, USA) was chosen. However, since the objective of this work was to design a system which could monitor temperature in two areas of a delivery van in parallel, a second communication bus would have to be employed. The literature has shown that the DS18B20 temperature 1-Wire probe (Maxim Integrated, San Jose, CA, USA), noted for its low cost and accuracy, has been widely employed for IoT temperature monitoring solutions, especially those pertaining to food loss and waste monitoring [81]. Thus, this sensor was selected as the second probe for the setup to allow monitoring in the chill area of vans in addition to their freezers. The sensor has an operating voltage of 3.3–5 V and ±0.5 °C accuracy. To allow flexibility on the installation location of the logger, the DS18B20 sensor was purchased on a 3 metre length to ensure it could be routed to the freezer area of the van. From official documentation from the sensor supplier, on cable lengths greater than 1 m, the sensor required a 5 V supply due to the voltage drop caused by the increased resistance which occurs on longer cable lengths. Given that $V_{drop} = I \times R$, the voltage drop will increase as resistance increases. Using the resistance of a length of material formula $R = \rho \frac{l}{A}$, where ρ is the conductivity of the cables material, l is the length of the cable, and A is the cross-sectional area of the cable, it is demonstrated that as the length of the cable extends, the resistance of it also extends. Hence, the longer the cable, the larger the voltage drop.

However, the Eagle logger only had a 3.3 V supply so a voltage regulator had to be added to the circuit, which would step up the 3.3 V to 5 V. The 2119 (Pololou, Las Vegas, NV, USA) step up/step down voltage regulator (V_{in} = 2.7 V–11.8 V, V_{out} = 5 V) was selected and added to each of the DS18B20 probes. This DC–DC converter is a switched-mode power supply which uses a buck-boost topology to regulate the input voltage to 5 V output with +5/−3% accuracy. Its typical continuous output current is 500 mA when stepping up, and its quiescent current is less than 0.1 mA.

An onboard accelerometer is used to detect the movement and change device state from sleep to awake. GPS logging was handled on-board the Eagle device by the EVA-M8 module (uBlox, Switzerland). The Eagle processes the GPS recordings and provides a single binary bit to indicate if the logger has moved in the last five minutes. The intention of this feature was to allow logistics companies to track whether their road transport vehicles were in motion. Further details on the trip detection algorithm will be presented in the next section.

3.2.3. Trip Detection

For an IoT anomaly detection system to be useful for users in food logistics, alerts should only be sent to personnel when the perishable food is in transport. This is to avoid false alerting when, for example, the delivery vehicle is parked overnight and the refrigeration unit is not powered on. Through being able to detect a trip on the device, an alerting algorithm can be constructed which is only enabled if the vehicle trip status parameter is true, therefore ensuring warnings are only delivered when the vehicle is being used. Additionally, by having the functionality to detect a trip, the device can assume a low-power sleep state and only wake and commence recording once the vehicle is in motion. Putting the device in a sleep state while not in use will significantly reduce battery consumption, thus reducing the maintenance schedule requirements of the device.

In order to detect a trip, therefore, a trip detection algorithm was incorporated in this work. The algorithm works as follows. When the device is powered on, it assumes a low-power sleep state. The only component active in this state is an ultra-low current piezoelectric accelerometer, which is constantly monitoring the acceleration applied to the device. If the accelerometer records a reading above a user-defined jostle threshold, it causes an interrupt to be fired on the integrated circuit, changing the state of the logger from low-power sleep mode to broadcast mode. Once in broadcast mode, the logger obtains a GPS fix. The logger then waits for a user-specified length of time before acquiring a second GPS fix. If the second GPS location is not equal to the first GPS location, the vehicle is in motion. The logger updates the trip parameter to true and the process repeats, acquiring two GPS fixes a period of time apart and checking if they match. Note that there is a 'heartbeat' mode implemented on the logger to send data periodically even if it is not in motion. This allows the user to see that the equipment still has battery power and is operating as normal. The frequency of the heartbeat can be configured by the user. For the case of food transportation, 12 h has been chosen. The pseudocode for the algorithm is presented in Algorithm 1.

Algorithm 1: Device trip detection

```
// Initialisation
lowPowerMode = true;
lastRecording = time.now();
jostleThreshold = 1;                                  /* 1=65mG */
stationaryRecordingTime = 43,200 ;                    /* 43200 s = 12 h. */
deviceFrequency = 300 ;                               /* 300 s = 5 min. */
while devicePoweredOn do
    Accel ← readAccel();
    currentTime ← time.now();
    lastReading ← lastRecording;
    timeElapsed = currentTime − lastReading;
    if Accel ≤ jostleThreshold then
        if timeElapsed ≥ stationaryRecordingTime then
            getSensorData();
            lastRecording = time.now();
        end
    else
        lowPowerMode = false ;  /* Interrupt triggered by Accelerometer to wake
         device from sleep state. */
    end
    while lowPowerMode == false do
        GPSfix ← readGPS();
        device.sleep(deviceFrequency);
        updatedGPS ← readGPS();
        if updatedGPS != GPSfix ±threshold then
            trip = true;
            getSensorData();
            lastRecording = time.now();
        else
            trip = false;
            getSensorData();
            lastRecording = time.now();
            lowPowerMode = true;
        end
    end
end
```

3.3. The Processing Layer

The primary datastore for the anomaly detection system is provided by the software company Whysor (Netherlands), who specialises in Internet of Things solutions and Big

Data architecture. As visualised in the architecture diagram in Figure 1, the Whysor database is synchronised in real time from Digital Matter's cloud using an in-house developed database connector which handles the data transformation. The Whysor datastore was a PostgreSQL database.

To allow the analytics researchers on the project to perform data analysis on the collected data, a backup data store was created. This served two purposes. Firstly, it allowed the REAMIT project to own the data and give GDPR assurances to pilot companies that their data were being stored on a secure university server dedicated to the project. Secondly, each researcher had their own private instance of the database, allowing them to manipulate the data without affecting the historical records saved to the Whysor DB. The backup database was a Microsoft SQL Server database and was synchronised with the Whysor database in real time using an in-house developed API.

The SMS alerting system runs in the processing layer and allows the user to build rule-based algorithms to send alerts if particular criteria are met. Further details on the algorithm and parameters chosen will be presented in the next section. The SMS alerting was provided by Amazon's Simple Notification Service (SNS). The algorithm's parameters are configurable from the dashboard, which is part of the application layer.

3.4. The Application Layer

Whysor developed and supplied the dashboard for real-time monitoring and alerting, which was utilised by each pilot study in the project. The web dashboard was developed in *Node.js* and utilises the *Chart.js* chart library for visualisation. The dashboard is implemented using the responsive web design principles, meaning the website and each of the chart elements appropriately scale to the device it is being viewed on. This allows the dashboard to run on both desktop computer and mobile phone, allowing the end-user to access it on multiple devices and interpret data in real time. The dashboard is completely customisable by the end-user, who can choose how they wish to visualise various sensor data, whether it be via line charts, gauges, tabular, or static text format. As visualised in the architecture diagram in Figure 1, the dashboard's data come from the Whysor database. All data analysis and visualisation were performed in Matlab 2021b.

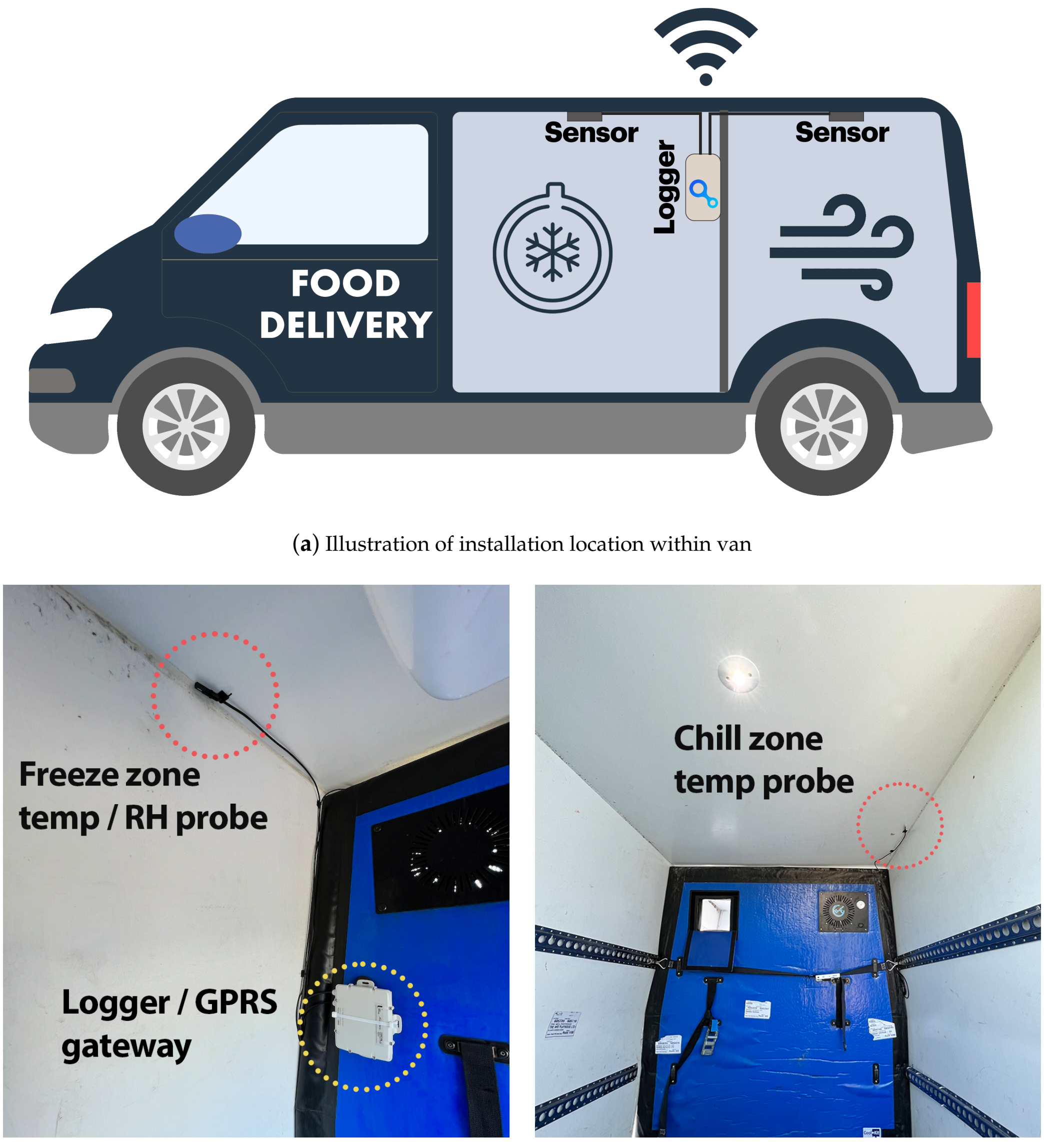
3.5. Real-World Testing

Musgrave Group Ltd. is an Irish food wholesaler, founded in Cork by the Musgrave brothers, Thomas and Stuart in 1876. It is currently Ireland's largest grocery distributor, with operations in Ireland and Spain, and they have estimated annual sales of over €4 billion. The company is still largely owned by the Musgrave family. Musgrave Northern Ireland is headquartered in Belfast, Northern Ireland. Musgrave clients include local restaurants, fast-food outlets, and convenience shops in northern Ireland, and they also operate multiple large cash and carry facilities for the general public. Musgrave maintains their own fleet of last-mile delivery vehicles to facilitate multi-drop deliveries to their business customers.

While performing deliveries of frozen goods and general perishables to their business customers, Musgrave noticed that the refrigeration units in the delivery vans operating in the greater Belfast area would occasionally break down without any indication to either the driver or the logistics staff at the warehouse. The temperature of the chilled and frozen food products inside the van would increase, surpassing the food storage temperature safety threshold, resulting in a van load of spoiled stock. Musgrave sought a system which could alert them of such anomalies.

The proposed system follows three requirements. Firstly, the transport vans should be connected to the cloud to allow for real-time data reporting/monitoring via a dashboard while the vans perform deliveries. Each of these vans have both a chill and a freeze compartment, both of which should be monitored throughout a journey. Secondly, the system should contain an alerting system which should send SMS messages to drivers and warehouse logistics staff notifying if any anomalies occur. These alerts should not be sent when the van is stationary, e.g., parked overnight, stopped while performing a delivery, etc. Thirdly, the power consumption of the proposed system should be such that maintaining the equipment does not become an arduous task.

Figure 2a illustrates the proposed layout of the dual-zone monitoring system. The sensors would be placed along the roof of the van in the two different refrigerated compartments separated by an insulated wall which contains a fan to push cool air through from the refrigeration unit based in the freezer compartment at the front of the van to the chill compartment in the rear of the van. Figure 2b shows the actual installation location. The logger was positioned on the insulted wall in such a way to ensure it would not interfere with the loading procedures of pallets followed by Musgrave.



(**a**) Illustration of installation location within van

(**b**) Actual location of logger and sensors within the delivery van

Figure 2. Planned and actual installation location of the IoT anomaly detection system.

For the field testing of the IoT system, it was decided to run the sensor on battery power to reduce the invasiveness of the installation. Each of the loggers were deployed with 4 $\times$ C cell long-life power alkaline batteries, each with a capacity of 7800 mAh.

In order to ensure minimal battery consumption was achieved, each logger deployed with the grocery distributor had the trip detection algorithm outlined in Section 3.2.3 enabled, which puts the logger in a low-energy sleep state when it is not in motion. The parameters chosen for the logger was a heartbeat signal every 12 h while out of a trip, and while in a trip, recordings were made and uploaded every 5 min. A GPS timeout of 60 s was chosen in order to reduce unnecessary battery consumption.

4. Results

The IoT temperature anomaly detection system was deployed in three of the grocery distributor's last-mile delivery vehicles in Belfast, northern Ireland, in April 2022. The analysis presented in this section was completed after 6 months of recording data. By this stage, the three vans had cumulatively recorded 3154 journeys, on average 10.2 journeys per day.

4.1. Dashboard for Real-Time Vehicle Monitoring

Each member of the logistics management team at the grocery distributor was given user credentials to access the monitoring dashboard. The dashboard allows its users to view and gain insights on the real-time data associated with all of the users assets in one centralized location. Once logged in, users are presented with the dashboard as shown in Figure 3. Users of the dashboard can only view the dashboard and respective sensors that they have been given access rights to, meaning the system is scalable to multiple companies. Each van being monitored is easily identified for the user on the dashboard using both the van model and vehicle registration. The interface shows the real-time readings of the environmental parameters (temperature and humidity), battery voltage and trip detection. A 1 reported by trip tells the user the vehicle is currently in motion, while a 0 tells the user the vehicle is stopped. In the corner of each element, the time of last update is visible.

The interface shows the temperature in all zones where sensors have been installed as well as the thresholds for the gauges (red-orange-green). The temperature thresholds were set according to the company's needs. The gauges provide a quick, easy to decipher visualisation into the transportation condition of the food. Green indicates that the food is being transported correctly, yellow indicates that the temperature is above the ideal temperature range but still does not compromise food quality and red indicates alarming status, and an automatic notification (Figure 4) is sent to personnel for timely necessary action. Further details on the notification system are discussed in the next section.

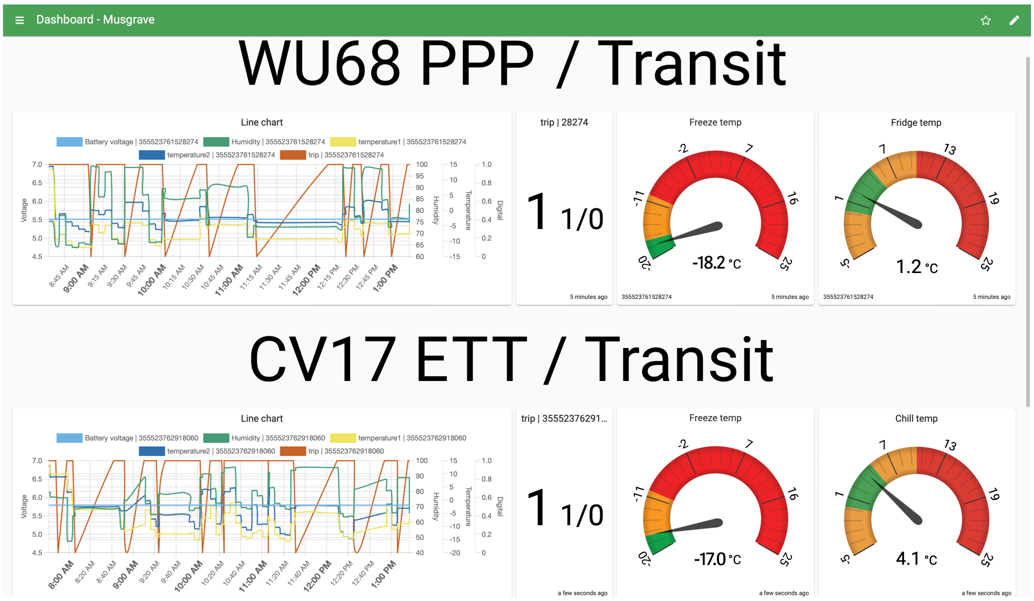
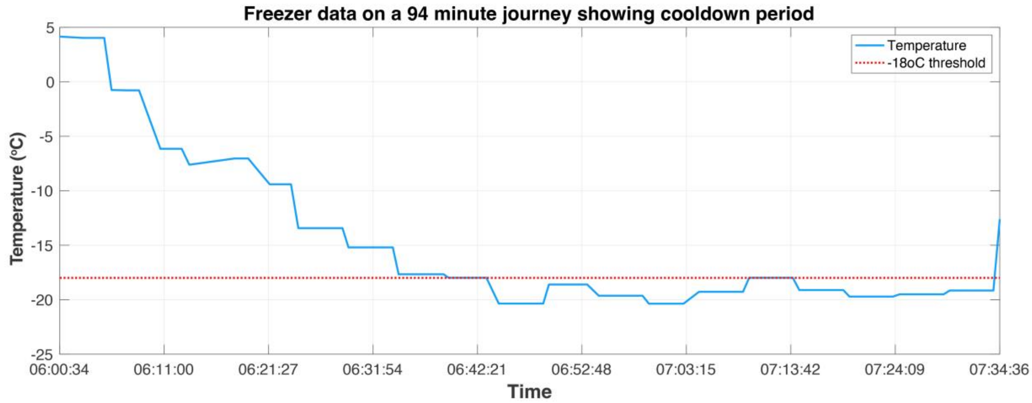


Figure 3. Developed dashboard shows environmental parameters in real time.

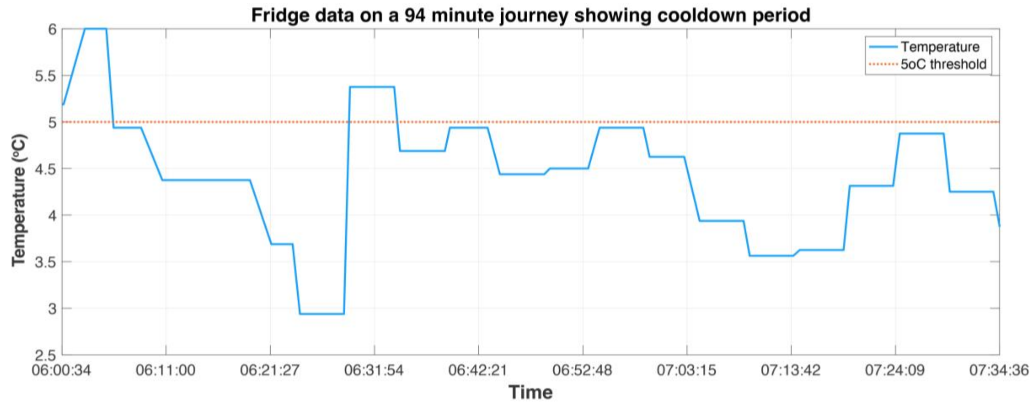
Figure 4. Anomaly alerting system.

4.2. Anomaly Alerting

After 179 days of continuous operation, the three IoT loggers had cumulatively recorded 49,839 datapoints monitoring the chill and freeze zone conditions of the last mile delivery vans operated by the grocery distributor. The distributor operated a multi-drop delivery from the vans, and the average duration of each delivery was 16.2 min. To effectively deploy an alerting system that notified the company of refrigeration anomalies in the delivery vehicles, it was necessary to evaluate the cool-down period of the refrigerators, i.e., the amount of time that it took for the vans to reach the desired temperature. The reason for this was to avoid alerting during periods where no anomaly or malfunctioning was occurring, and the refrigeration units were merely cooling from ambient temperature to chill/freezing temperatures. Using the data recorded by the grocery distributor during deliveries, a preliminary analysis was carried out to estimate the cool-down period length of the delivery vans. The desired temperatures the vans were to operate at were 5 °C in the fridge compartment and −18 °C in the freezer compartment. Analysis from the recorded data showed that it took approximately 35 min for the vans to appropriately cool down (Figure 5); thus, alerts should be configured in such a way that they were only sent after this initial period had passed. To do so, an alerting algorithm was implemented that only triggered the alerting system after 35 min.



(**a**) Freezer analysis



(**b**) Fridge analysis

Figure 5. An example of fridge and freezer cooldown periods.

To avoid false alerts being sent while the vehicle was stationary, the trip variable reported by the trip detection algorithm presented by Algorithm 1 in Section 3.2.3 was used for the alerting algorithm. Given the trip status and the desired temperature thresholds, the alerting algorithm was designed as follows.

Each time the logger produces a recording, the temperature readings and trip information are passed to the alerting algorithm. The cool-down period and temperature thresholds of the fridge and freezer are configurable by the user. In this case, 35 min has been chosen as the cool-down period, −18 °C has been chosen for the freezer threshold, and 5 °C has been chosen for the fridge threshold. Given the user-specified cool-down period and frequency of sensor recordings, the total number of repeated true trip parameter recordings required is calculated. The algorithm then checks to see if the vehicle has been in motion for the specified number of recurring recordings. Only if the vehicle has been in motion constantly during the recurring recording period does the algorithm progress to the next stage: threshold checking. If at any point the vehicle stops moving and the trip parameter becomes false, the counter is reset and a further recurring recording period (in this case 35 min) will have to elapse before the algorithm progresses to threshold checking.

At the threshold checking stage, anomalies in the sensor equipment are accounted for by ensuring two repeat values abusing the user-specified temperature threshold are recorded. If the temperature threshold is broached twice in a row, an alert is sent. The algorithm behaves the same way for both the chill and freeze temperatures. Note that the cool-down period can be specified for each of the zones, meaning the user can define a longer cool-down period before alerting begins for the freezer and a shorter cool-down period before the alerting algorithm is triggered for the fridge zone. Examining the data presented in Figure 5, it is probable that the grocery distributor would want to avail of this functionality. Notice that while the freezer takes 35 min to reach the appropriate chilled temperature, the fridge has reached the desired temperature within 5 min. Given that perishment occurs more quickly transporting refrigerated goods rather than frozen goods, more timely alerts for this area of the van are desirable. In this example, the freezer cool-down period could be set as 35 min and the fridge cool-down period could be set at 5 min. The pseudocode for the alerting system is presented in Algorithm 2.

Algorithm 2: Anomaly alerting

```
Function Alert(trip, temperature, coolingZone):
    coolDownPeriod = 35;
    Frequency = 5;
    numOfRecordings = coolDownPeriod/Frequency;
    notInTrip = 0;
    if coolingZone == "freezer" then
        tempThreshold = −18;
        alertName = "freezer";;
    else
        tempThreshold = 5;
        alertName = "fridge";;
    end
    for i = 1 : numOfRecordings do
        if trip(i) == 0 then
            notInTrip = notInTrip+1;
        end
    end
    if notInTrip == 0 then
        for i=1:size(temperature −1) do
            if size(temperature)>1 then
                if temperature(i) ≥ tempThreshold && temperature(i+1) ≥ tempThreshold then
                    Alert = alertName;
                else
                    Alert = 0;
                end
            end
        end
    end
    return Alert;
```

Alerts can be sent via email or SMS to the end-user of the system. Figure 4 shows an example of the automatic notification which is sent to personnel for timely necessary action if temperature abuse is noted. A descriptive message detailing the van model, registration, if the error has been recorded in the freeze or chill compartment, and the user-specified temperature threshold that has been abused is sent to the personnel. Additionally, the message embeds a link to the organisation-specific dashboard so that the user can quickly access the live and historical data from their mobile phone and identify if a problem has really occurred.

It is worth noting that alerts are not continually sent if the vehicle remains in motion and the threshold continues to be abused. Once one alert is sent, a timeout period of ≈90 min is activated before a follow-up alert is sent. This feature is to prevent end-users' mobile phones from being spammed with text messages.

4.3. Battery Life Analysis

The logger's were deployed with 4 × C cell Zn-MnO_2 alkaline long life batteries, each with a capacity of 7800 mAh and manufactured by Varta [82]. After 179 days of continuous operation, one of the loggers installed in a delivery van ran out of battery. In its lifetime, it recorded 29,342 datapoints representing 1812 journeys: approximately 10 journeys per day. Figure 6 shows the degradation of the batteries over the lifetime of their discharge in blue. A degree one polynomial regression (i.e., a linear regression) is applied and is shown as a dashed black line laid on top to demonstrate the linear decay throughout the lifetime of the battery. Notice that near the end of the battery's useful life, the battery starts to degrade much more quickly, as to be expected in alkaline performance [83].

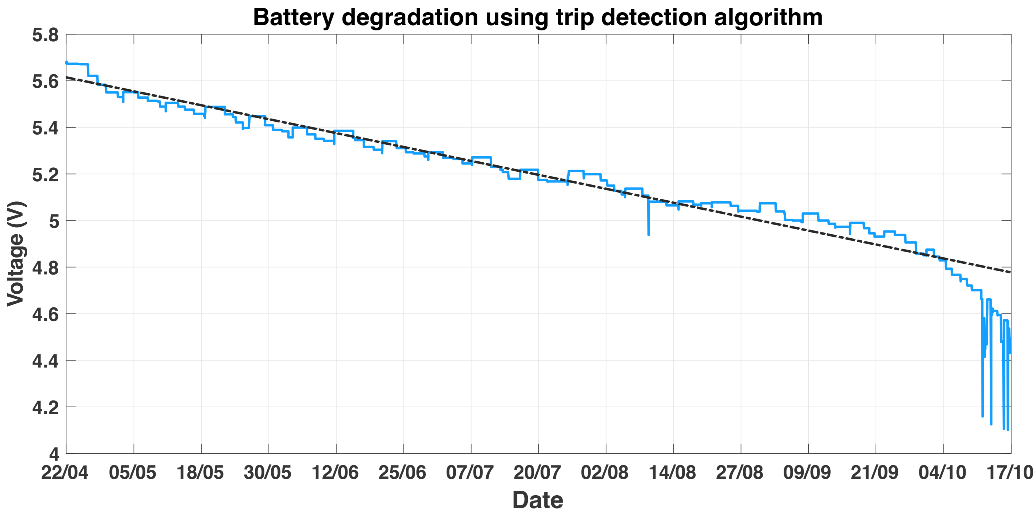


Figure 6. Battery degradation analysis.

The battery's starting voltage was 5.672 V. The last recorded voltage by the logger before the batteries no longer had the capacity to power the device was 4.493 V. Thus, during its useful life, the logger used 1.179 V. Given that the number of recordings made was 29,342, the average voltage consumption per recording is calculated using Equation (1).

$$recordingVoltage = \frac{powerConsumed}{totalRecordings} \tag{1}$$

In this case, the resulting recording voltage per reading was equal to 4.02×10^{-5} V.

To demonstrate the benefit of the trip detection algorithm on battery conservation, the battery performance of the logger with trip detection enabled is compared to that of a logger without trip detection enabled. Without trip detection enabled, the logger uploads data every 5 min regardless of whether the vehicle is in motion or not. This results in 288 recordings made every 24 h, every day, while there is enough battery capacity to power the device. Using the average voltage consumption per recording, an approximation of how long the logger would have lasted without trip detection enabled can be made. Assuming that the logger uses the same power consumption whether trip detection is enabled or disabled, a battery life estimate can be provided using Equation (2).

$$daysOfRecording = \frac{powerConsumed}{recordingVoltage \times 288} \tag{2}$$

resulting in an estimated days of recording of 101.8 days.

To check the accuracy of this estimate, bench testing was performed on one of the devices. The logger was prepared to the same specification as the loggers deployed with the grocery distributor, and it was running the same firmware revision. The only difference between the two setups was that trip detection was disabled on the logger being used for battery performance testing. With trip detection disabled, the logger made and uploaded recordings every 5 min, regardless of motion. Given that the decay of the alkaline battery is linear (except at the end of its useful life), the testing can be applied at any battery voltage and be used as an insight into the life expectancy of the logger. In this case, the bench test began with a starting voltage V = 5.335. The bench testing experiment was performed for a period of 28 days. At the end of the testing, the final voltage was V = 5.039. In total, therefore, the logger used 0.296 V over 28 days. Over this period, it had made 8104 recordings, presenting an average voltage spend of 3.65×10^{-5} V per recording.

For the updated estimate based on this usage, the period required for the logger with trip detection enabled to use 0.296 V was checked. Upon analysing the data, it was found that the battery of the logger deployed with the food company took 66 days to use the same voltage. Over this period, the logger had made 12081 recordings, resulting in an average recording voltage spend of 2.45×10^{-5} V per recording.

The difference in these average recording voltages is by a factor of 1.4907, meaning the device with trip detection disabled is using power 1.5 times more quickly than the device which has it enabled. This is most likely because the device does not go to sleep, meaning components stay powered on during the 5-min intervals when recordings are not taking place.

The original estimate of battery life with trip detection disabled can now be updated using the results from this analysis. Given that power consumption during the linear decay phase is ≈1.5 times greater than that of trip detection logger, the new estimate for the total number of recordings during the batteries' total useful life is 29,342/1.4907 = 19,683 data points. At 288 recordings per day, the life expectancy of the logger without trip detection enabled is estimated at 19,683/288 = 68.35 days.

This is a 61.8% decrease in performance from the logger with trip detection enabled, which recorded data for 179 days in total before battery exhaustion. Figure 7 visualises the difference in battery degradation between the logger which has trip detection enabled (blue plot) versus the logger which has it disabled (purple plot). From this, the ≈2.5 times performance increase the algorithm has on battery life can be observed.

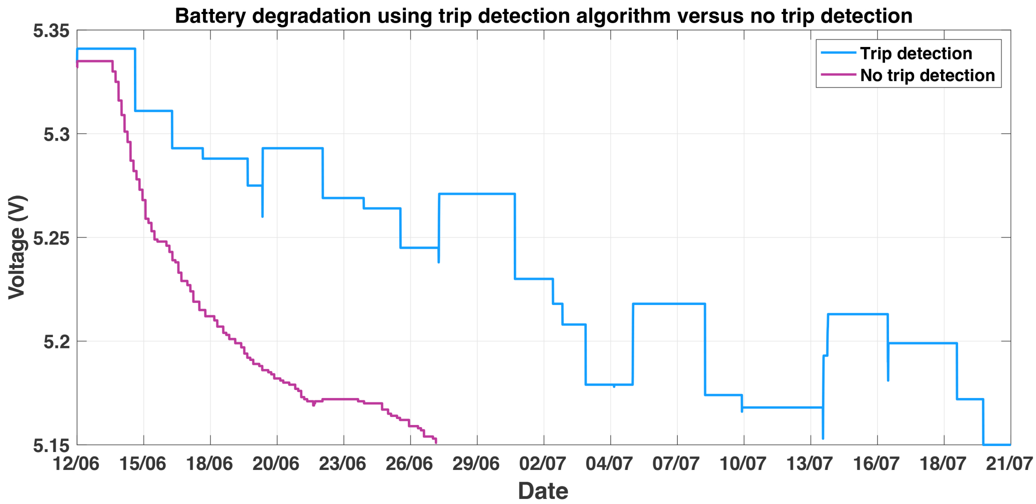


Figure 7. Battery degradation with trip detection enabled and disabled.

It is worth noting that the logger deployed in the refrigerated van with trip detection enabled is additionally exposed to lower temperature levels which can negatively influence the battery voltage and capacity. This is due to the slowdown of electrochemical reactions and decrease in the ionic conductivity in certain battery components [83]. Therefore, the results of the trip detection algorithm may be exacerbated further if battery analysis testing was conducted on a logger deployed in the refrigerated van with trip detection disabled. Further research is required to see if this is the case.

5. Discussion

The development of real-time IoT monitoring systems for perishable food transportation provides a vast number of managerial opportunities for supply chain personnel. With the availability of real-time data giving insights into the transportation conditions of perishable stock, logistics managers of agri-food businesses can perform pro-active data-driven business decisions if anomalies occur. However, to date, most systems rely on either the manual human monitoring of data or device-specific platforms (Android [70], Windows operating system [55] or RFID reader [56]) to detect anomalies.

The real-time anomaly detection system presented in this work mitigates both of these restrictions. The system has been shown to provide intelligent anomaly alerting based on vehicle motion and temperature threshold abuse. In addition to the trip-based alerting, to aid in minimising false warnings, the developed system accounts for detection anomalies by requiring two readings in a row to broach the threshold before sending the alert. Compared to other studies in the field, this paper has shown a fully implemented IoT system with a real-time monitoring application accessible on any device and a platform agnostic warning system if anomalies are detected during cold chain transportation. Companies are typically concerned about whether IoT can work well with their business process, strategic management, and supply chain flow, as well as preceding information systems. However, the proposed system overcomes these compatibility requirements that can act as a blocker toward technology implementation by adopting a framework available for mobile and computer devices. On the other hand, the platform agnostic warning system proposed can also handle the data complexity challenge. IoT monitoring technologies involves a vast data processing throughout its usage that requires not only skilled and knowledgeable users but also facilitating conditions in terms of data management such as tools and networks. In this study, a user-friendly dashboard is used, as shown in Figure 3. In addition, while this paper validates the IoT RTAD system with a food wholesaler, the platform has been designed in an agnostic manner allowing it to be expanded to various logistics applications.

The anomaly detection system provides real-time information to logistics personnel, allowing them to redirect produce, if required, to a closer depot or a different business customer, resulting in the reduced spoilage or wastage of food stuffs. There are additional managerial benefits of implementing this IoT monitoring technology which should not be overlooked. As well as the economic and environmental impact that reducing food spoilage has on a business, IoT monitoring technologies increase the cold chain security and integrity. This leads to better client trust and relationships as there is a single source of truth allowing any stakeholder in the supply chain to refer back to the conditions that shipments have been exposed to. In addition, researchers and practitioners agree that IoT-enabled supply chain gains more benefits, including real-time information sharing, cost reduction, efficiency, transparency, traceability, and sustainability, than the one lagging disruptive technology.

However, the literature suggests some factors affecting IoT adoption in food supply chain management. Potential IoT adopters are still concerned by the hardware and infrastructure needed to deploy IoT technology in their supply chain management [84]. IoT adoption must be followed by providing tools, sensors, gateways, mobile devices, protocols, applications, and connectivity to establish an environment that facilitates information sharing among all stakeholders, and some companies cannot afford to build and maintain such an IoT environment. The cost of adopting IoT remains a top challenge for the industry, making it another vital factor to be considered. A company generally is more willing to adopt IoT technology when the device cost and electricity bill decrease, some studies have conveyed. Therefore, the IoT adoption should consider whether the spent cost is worth the benefit.

As previously mentioned, cost is a limiting factor in the adoption of IoT-enabled systems, especially for small and medium-sized businesses. For this reason, in this study, the proposed technology uses cost-effective components to ensure the rollout of monitoring technology is cost-feasible for the business. Additionally, the system operates on preexisting telecommunication infrastructure mitigating potential network layer overheads presented by other systems.

Many systems in the literature use fixed power supplies for their gateway unit [68,71]. Although this suits the use case of a refrigerated van or lorry such as that of the validation case company, there are applications where a power supply for the IoT system is either not present or inaccessible. For example, in the case of temperature-sensitive donor milk delivery [85], the transportation method is a motorcycle where a power supply to the temperature-sensing unit is unavailable. While some portable systems have previously used mobile phones as a gateway device for data capture and upload [61,64,69], constant mobile device charging and the pairing of sensors with driver changes increases the likelihood of missed data capture. The system presented in this paper was therefore designed with ease of use and energy efficiency in mind, operating without any intervention from the driver. Results from the battery testing show that by putting the device to sleep while not in use, a minimal device maintenance schedule is also achieved, thus keeping the costs of technology upkeep for the business to a minimum.

The sensitivity of the trip detection algorithm is configurable by adjusting the timeout between GPS readings. For Musgrave, NI, the detection window was every 5 min, meaning this was the time between GPS location checks to detect if the van was in motion. However, if the system was deployed in a traffic dense city, the users of the system could increase this parameter accordingly. Extending the window between trip checking could help ensure that the trip status remains valid in the case of a traffic jam. The algorithm, however, does not consider breakdowns in the van. Due to the way alerting is implemented, if the van completely broke down, the logistics staff would not receive an alert about potential temperature abuse as the algorithm relies on vehicle motion being true. Future work will seek to add geofencing functionality to the alerting algorithm. Through the establishment of the base location of the vans, the alerting system could be expanded to offer a breakdown monitoring mode if, for example, the van had been stationary for one hour and it was not located at the known home location of the van. Rather than not uploading data due to a lack of vehicle motion, the breakdown monitoring mode could continue to upload data in 5-min intervals, ensuring the integrity of the products.

Another limitation of the work presented in this paper is that different sensor placement locations were not explored during the installation and testing of the IoT RTAD system. The location of sensor placement chosen in this work was upon consultation with refrigeration logistics specialists at Musgrave, NI, who had prior knowledge installing cold chain transportation temperature monitoring equipment. However, previous studies have indicated that the temperature inside the refrigerated equipment is heterogeneous [11]. For example, some suggest that the most accurate ambient temperature insights are provided by monitoring the 'air on' of the refrigeration unit, which is where the ambient air is drawn into the refrigeration unit after circulating the entire chill area. This contrasts the chosen installation location of the sensors in this work, which were placed along the roof, approximately in the middle of each zone. Furthermore, the relationship between the core product temperature and the ambient temperature recorded by the monitoring system in this case is unknown. Therefore, additional work needs to be undertaken, trying different sensor locations and monitoring how the ambient temperature recorded changes.

The warning system currently deployed, which offers alerts via SMS or email, can also be a limitation. It is sometimes the case that logistics staff working in warehouses do not have GSM cell coverage, rendering alerts sent on the SMS system undeliverable. While the email system provides an alternative alerting mechanism to ensure that while out of cell coverage but within WiFi range the end-user still receives alerts, many end-users do not have push notifications enabled for email due to the quantity they receive on a daily basis. Future work will focus on expanding the alerting system to a smartphone application such as that of [70] so that push notifications can be delivered while in the range of WiFi. Additionally, technologies such as the real-time anomaly detection system presented in this paper could be deployed at each stage of the cold chain to allow for the uninterrupted monitoring of perishable goods. This would result in anomalies being detected not only during transportation but also during storage, at the retailer, etc. Each of these efforts could further reduce potential food wastage in agri-food businesses.

6. Conclusions

This work demonstrated the application of an energy-efficient battery-powered IoT-based alerting solution for the temperature anomaly detection of refrigerated food products during transport. The system was further validated in a real-world scenario by utilising the delivery vehicles of a last-mile grocery distributor in northern Ireland in which the loggers were installed. The alerting system was specially configured so that it could effectively notify staff members in a timely manner of anomalies occurring in the refrigerators but only under the following circumstances: when the vehicles were in operation and moving, and once they had appropriately cooled down and reached the desired temperatures of refrigeration, which is achieved after 35 min. An algorithm was developed to configure the dedicated alerting system so that it was only triggered once the conditions were met. To improve user technology acceptance as well as maintenance requirements and mitigate environmental impact related to resource consumption, another algorithm was designed and implemented to reduce the battery consumption of the IoT devices. This was carried out by means of enabling a trip detection mechanism based on acceleration and GPS information.

Battery life analysis was performed to determine the impact of the trip detection algorithm on trip-detection enabled loggers versus loggers without it. Results estimate a life expectancy performance increase of roughly 162% using the logger with trip detection enabled versus a logger without trip detection, increasing usage between battery changes from 68 to 179 days. The logger deployed in the refrigerated van with trip detection enabled was exposed to lower temperatures which may have negatively affected the battery voltage and capacity, and if the bench testing on trip detection had occurred in the same conditions, the results could have shown a higher difference in battery consumption.

The trip-detection algorithm was effective in reducing battery consumption and enabling loggers to remain operative for longer without a replacement, thus decreasing the total economic resources and environmental impact of the system in the long run. Additionally, the trip detection algorithm was also utilised to provide intelligent alerting for the anomaly detection system.

Future work will validate the battery usage of loggers without trip detection in a real-case refrigerated scenario to account for difference in temperature. Additionally, the sensor setup can be expanded upon to incorporate a door contact sensor so that alarms can be sent to driver and warehouse staff if it has been left open during a delivery. This will be especially relevant for multi-drop grocery distributors with perishable stock remaining in their vans as they perform multiple deliveries before returning to the warehouse.

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Raman Spectroscopy Application in Food Waste Analysis: A Step towards a Portable Food Quality-Warning System

Omar Hussein Dib [1], Ali Assaf [1,*], Alexia Pean [1], Marie-Jose Durand [1], Sulivan Jouanneau [1], Ramakrishnan Ramanathan [2] and Gérald Thouand [1]

[1] Nantes Université, ONIRIS, CNRS, GEPEA, UMR 6144, F-85000 La Roche-sur-Yon, France
[2] Essex Business School, Southend Campus, Elmer Approach, Southend-on-Sea SS1 1LW, UK
* Correspondence: ali.assaf1@univ-nantes.fr

Abstract: Food waste is one of the main problems contributing to climate change, as its piling up in landfills produces the greenhouse gas methane. Food waste occurs at every stage of food production; however, a major source of food waste occurs at businesses that supply food to consumers. Industry 4.0 technologies have shown promise in helping to reduce food waste in food supply chains. However, more innovative technologies, such as Raman spectroscopy, hold great promise in helping to reduce food waste, although this has largely been ignored in the literature. In this context, we propose a portable Raman platform to monitor food quality during transportation. The developed system was tested in conditions mimicking those present in a refrigerated truck by analyzing chicken samples stored at temperatures of 4 °C. Raman spectra were acquired for non-packaged and packaged samples over the duration of 30 days resulting in 6000 spectra. The analysis of Raman spectra revealed that the system was able to detect noticeable changes in chicken quality starting on day six. The main Raman bands contributing to this change are amide I and tyrosine. The proposed system will offer the potential to reduce food losses during transportation by consistently checking the food quality over time.

Keywords: food waste; Raman spectroscopy; food quality; protein

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1. Introduction

The estimated global food waste recorded by the United Nations Environment Programme in 2021 was about 931 million tons [1]. The causes of food waste are abundant and occur from farm to fork, i.e., during production, processing, distribution and selling, and lastly, consumption. Furthermore, the increasing concerns around climate change, land use, water use and loss of biodiversity have encouraged researchers and scientists to come up with new rapid and accurate methods to assess food quality and prevent food waste along the production–consumption chain.

Traditionally, evaluating food quality is done using a direct approach, particularly by conducting a microbial analysis. This analysis is necessary for determining the shelf life and quality loss of a food product [2]. Since microbial load and microflora composition are quite important parameters for detecting food quality, such analysis is impossible to execute at certain stages of the food and marketing chain, such as during transportation. Other alternatives would be the use of indirect approaches such as Industry 4.0 technologies which are already being used to help reduce food waste in food supply chains [3]. These technologies generally help monitor storage conditions such as temperature, humidity, light, and vibration, with the help of Internet of Things sensors (IoT). These sensors measure the required parameters and send them to the cloud for remote monitoring. In case the monitoring detects unacceptable storage conditions, then rapid corrective actions are taken (e.g., checking the temperature control mechanisms) in order to guarantee the freshness of food. While these IoT sensors are useful, they do not capture the freshness of food directly, but rather via related parameters such as temperature or humidity. Instead, there are more innovative technologies, such as Raman spectroscopy, that analyze food directly and are able to measure the freshness of the food more directly.

In recent years, Raman spectroscopy advancements have opened new research insight by allowing rapid and non-destructive analysis. This optical method, which relies on the inelastic scattering of light, is used in several domains of applications: medical, pharmaceutical, food, and microbial detection [4–7]. The main objective of Raman spectroscopy is to simplify the analysis process and to reduce the investigation time of samples. This untargeted screening of food samples aims to evaluate the characteristics of a given product (by the production of a structural fingerprint revealing almost all chemical components, including nucleic acids, carbohydrates, lipids, and proteins) and to relate its spectral fingerprints to distinctive traits such as nutritive value, adulteration, or quality of food. Among spectroscopic methods, Raman and Surface Enhanced Raman Scattering (SERS) are considered promising techniques for food analysis. Both offer a rapid, nondestructive and label-free analysis. The difference between the two methods is that SERS has higher sensitivity allowing the structural detection of low-concentration substances which are difficult to detect using traditional Raman Spectroscopy [8,9]. SERS higher sensitivity is obtained by using an enhancing substrate such as gold (Au), silver (Ag), or copper (Cu). However, the use of such substrate in determining the quality of a food product can complicate the analysis step, especially if the food is packaged. Such a factor makes traditional Raman Spectroscopy preferable over SERS.

Traditional or native Raman Spectroscopy is considered a promising candidate for monitoring food quality, especially meat products. For instance, this type of spectroscopy is capable of studying modifications at the level of secondary protein structures such as amide I (1650–1680 cm^{-1}), and amide II (1262–1313 cm^{-1}) regions, as well as C-C groups (940–1070 cm^{-1}), C-H groups (1440–1457 cm^{-1}), and amino acids (640 and 850 cm^{-1}) [10,11]. Also, Raman spectroscopy is widely being used in the determination of meat organoleptic properties [12], spoilage [13], pH [14], identification of meat from different animal species [15,16], and studying meat quality from different slaughter animals including chicken [11,17,18]. All the latter studies show that Raman equipment monitoring meat quality is fairly well developed for laboratory testing. Nowadays, and thanks to the technological advancement of Raman, a trend is being noted worldwide towards the promotion of automated quality control [19]. For instance, portable Raman systems have been developed to be used in the meat industry [20]. Moreover, Bauer et al. [21] and Fowler et al. [22] used portable Raman spectroscopes to study the tenderness and sensory characteristics of beef. In spite of the latter, their use remains timid in food applications, especially in the reduction of food waste. In addition, the literature on food waste has largely ignored the use of such highly innovative technology so far.

The primary contribution of this paper is to showcase the use of Raman spectroscopy for fighting food waste. The main limitation of applying Raman spectroscopy is the huge size of the equipment, which makes it practically impossible to use this technology in trucks. However, the team of authors has pioneered the development of a portable version of Raman spectroscopy. This is another huge contribution of this paper. We showcase the use of a portable Raman, placed and tested in a refrigerated chamber to mimic the conditions present in a refrigerated truck transporting chicken product from one outlet to another.

2. Materials and Methods

2.1. Sample

About 30 packed cooked boneless chicken breasts with the same production and expiry date were purchased from a local store. The samples were packed under a modified atmosphere (O_2 = 68%, CO_2 = 26% and N_2 = 6%). After purchasing, the packages were stored directly in a fridge at 4 °C. The samples were then distributed in two stages.

Stage I is considered as a proof of concept, where the sole purpose of this stage is to check which Raman bands are responsible for the shift in chicken quality. In this stage, the chicken breast was removed from the package each day for 30 days and its Raman spectra were measured.

Stage II is the validation stage; this stage was necessary to prove that the proposed Raman system can still check the quality of the chicken through the package (made from low-density polyethylene, LDPE), and to determine on which day there was a noticeable change in the chicken's quality. In this stage, only one of the packed samples was utilized, and the chicken breast wrapped in LDPE was measured directly by Raman spectroscopy for 30 days. About 13 zones were carefully chosen and studied on the surface of the wrapped sample (Figure S1), and the zone with the most informative region was selected for executing stage II.

Stages I and II were done in refrigerated conditions at 4 °C and the spectral measurements were done directly on both surfaces without any pre-treatment (such as fat removal, washing, or mincing).

2.2. Raman System and Measurement

An automatic portable Raman system was used in this study (Figure 1). This system consists of a QE Pro-Raman spectrometer (Ocean Optics, Netherlands) having a dynamic range of 85,000:1 and System SNR: 1000:1 with typical back-thinned CCD array miniature spectrometers cooling to −40 °C below ambient air; Laser source of 785 nm excitation wavelength (Oxxius, France); InPhotonics RPB785 fiber-optic probe consisting of two single fibers (105 μm excitation fiber and a 200-μm collection fiber) with filtering and steering micro-optics contained in a polyurethane jacket; Motorized 3-axis (X, Y, Z) platform (Standa, Opton Laser International, France) with a sample holder; Dark enclosure specifically made to prevent light from interfering with the fiber-optic probe head (numeric aperture: 0.22); Computer running OceanView software (Ocean Optics, Netherlands), and Libximc cross-platform library to control the motorized stage. The whole system was placed in a cold chamber at 4 °C for 30 days.

Figure 1. A dark enclosure (**A**) including the automated Raman system parts: (**B**) QE Pro-Raman spectrometer, (**C**) InPhotonics RPB785 fiber-optic probe, (**D**) Motorized 3-axis (X, Y, Z) platform, and (**E**) computer running OceanView software and Libximc.

Raman spectra were then collected using the following parameters: laser power of 250 mW, a focal distance of 2 mm with an integration time of 5 s. The spectral resolution was 5 cm^{-1} in the measured wavelength range of 200–4000 cm^{-1}. The dark spectrum subtraction was performed during each spectral acquisition. For each stage, 100 spectra were collected per day, with the help of the motorized stage, with a total of 3000 spectra over 30 days. The temperature of the chamber was taken two times per day over 30 days to ensure that the temperature did not rise above 4 °C.

2.3. Spectra Pre-Processing

Raman spectra were processed using Opus software (Bruker optics GmBH, V 7.2, Germany) and MATLAB software (version R2019b, MathWorks Inc, Natick, MA, USA). The raw data, of a spectral range of 200–4000 cm^{-1}, was first cut in the spectral zone of 500–3000 cm^{-1}. Then, all cosmic spikes presented in the defined spectral range (500–3000 cm^{-1}) were manually eliminated before applying data treatment. All spectra were then baseline corrected using an elastic concave method (64° and ten iterations), smoothed based on the Savitzky-Golay algorithm, and lastly normalized using min–max normalization.

2.4. Data Analysis

After spectral processing, the treated spectra were subjected to multivariate data analysis, specifically, Principal Component Analysis (PCA). PCA is a technique commonly used to transform large datasets into two smaller sets, referred to as the score matrix and the loading matrix. This orthogonal transformation allows the observation of trends and clusters, and uncovers the relationship between observations and variables by plotting the principal components (PCs) and the loading plots [23]. Accordingly, the number of PC components to be used was determined using a scree plot. PCs were represented by scatter plots and the correlation among the variables can be inspected through loading plots.

PC scores (PC1 score of stage II) were subjected to Kruskal Wallis (KW) test. This test is a non-parametric test and is used to compare samples from three or more groups of independent observations [24]. It was selected to establish statistical significance (p-value < 0.05), and also because it is more stable to outliers. PCA and KW were computed using the SAISIR Package [25]. All statistical analysis was performed using MATLAB software (version R2019b, MathWorks Inc, Natick, MA, USA).

3. Results and Discussion

The portable Raman system was tested in two stages to confirm its ability to monitor the quality of chicken over 30 days. These tests are essential in order to verify that the Raman sensor can give reliable results under any circumstances before launching it in the field. The main obstacle confronted was the introduction of a package layer between the probe (laser) and the sample (chicken breast).

3.1. Detecting Changes in Chicken Quality (without Packaging) by Raman Spectroscopy

The first stage of testing included the study of chicken fillet quality with respect to time (30 days) and temperature (4 °C). At this stage, Raman spectra were obtained directly on chicken (without packaging). Before analyzing the data acquired by the Raman sensor, Table 1 illustrates the various molecular vibrations present naturally in the chicken breast Raman spectrum [10]. For instance, the familiar Amide I bands, with their different configurations (α-helix and β-helix) presented at different Raman shifts, as well as amide III representing collagen at 1313 cm^{-1}, the C-H bending at 1440 cm^{-1}, and C-C stretch at 2906–3011 cm^{-1}. Additionally, other Raman bands can be observed when analyzing chicken meat that corresponds to aromatic amino acids such as phenylalanine at 1077 cm^{-1}, and tyrosine (Tyr) at 850 and 640 cm^{-1}. Vibrations from the nucleobase adenine (Ade) and S-S stretching can also be present. All of the latter stated bands, particularly those representing proteins, are the main contributors to the textual characteristics and functional properties of chicken meat, and they will help in highlighting the effect of storage on chicken quality [10,26].

Table 1. Familiar Raman bands present in chicken breast.

Raman Shift (cm^{-1})	Vibrational Mode
3011, 2914, 2895, 2854	C-H stretching
1658–1645	Amide I (α-helix)
1680–1665, 1640–1610	Amide I (β-helix)
1665–1660	Amide I (random coil)
1690–1680	Amide I (β-turn)
1457–1440	C-H bending
1313 and 1260	Amide III (collagen)
1240	Amide III (β-sheet and random coil)
1070	C-C stretching (phenylalanine)
850 and640	Tyrosine stretching-ring
750	Adenine stretching-ring
525	S-S stretching vibration

Other proteins, such as myoglobin or in particular the heme pigments of myoglobin, present in chicken or any other kind of meat can weaken the Raman signal by causing a common phenomenon faced in Raman analysis known as fluorescence background [13]. To acquire the best spectrum, as presented in Figure 2, the fluorescence background was omitted by using a baseline correction algorithm.

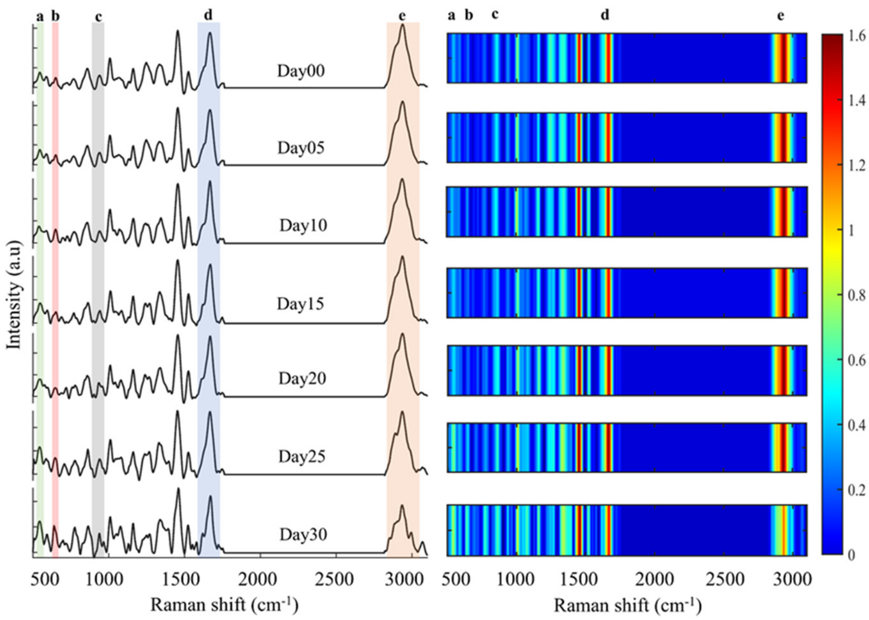

Figure 2. The variation in Raman spectra of chicken breast without packaging over 30 days of storage at 4 °C. The highlighted regions (a–e) represent the vibrational bonds that are changing in function of time. (a): S-S stretching, (b,c): Tyrosine, (d): Amide I (α-helix), (e): C-H stretching.

After spectral treatment, the average spectrum of each five days was taken and plotted. Figure 2 shows the changes detected in chicken Raman spectra over 30 days at 4 °C. Raman spectra obtained on Day 00 were considered as the standard or fresh samples and all other days were compared to it. Of all the Raman bands present in Table 1, five peaks were visually identified that seem to be changing with storage time, as shown in Figure 2. In addition, a pattern regarding the intensities of these peaks was noticed where S-S stretching (a) and Tyrosine (b and c) intensities increased, while those of Amide I (d) and C-H stretching (e) decreased as storage duration increased.

Although Raman signals are gradually changing, as shown in Figure 2, visual goings-over of these changes remain difficult. To have more information on the Raman spectrum changes caused by storage time, PCA multivariate statistical tool was applied to the Raman spectra (Figure 3). The first, second, and third principal components, or PC1, PC2, and PC3, carried the most spectral variances over 30 days. PC1 explained 30% of the variance, PC2 explained 25% of the variance, and PC3 explained the least with 5%. All other PCs contained less than 1% of the variance between samples. Figure 3 shows the PCA plot of the PC1, PC2 and PC3 scores and their loadings. The PCA plot reveals a separation of the samples based on their quality over time. PC1 clearly distinguishes the spectra of chicken obtained from the 25th to 30th day. This group (days 25 to 30) is separated from the other samples by having a positive sign with respect to PC1. This separation is also clearly observed on PC3 (see Figure S2) where the same group of samples (days 25 to 30) is distinguished from the other samples by having a positive sign on PC3. The main contributions for PC1 and PC3 were from the Tyr band (845 and 640 cm^{-1}) and S-S stretching vibrations (525 cm^{-1}), correlating with a positive sign of loadings (Figure 3B), and from the phenylalanine (1077 cm^{-1}), amide III (1311 cm^{-1}), amide I (1655 cm^{-1}) and C-H stretching (2906 cm^{-1}), correlating with a negative sign of loadings (Figure 3B). Based on the PCA results, the shift in quality in the last five days observed in Figure 3A is due to the decrease in the intensity of all correlated bands with the amide I band, and an increase in the intensity of anti-correlated bands such as Tyr. This increase is a result of the extra amino acids which were formed during storage due to microbial growth and autolysis of meat. Additionally, the decrease in the intensity of Amide I and III (also supported by PC2 scores and loadings) modes or the denaturation of protein is known to occur during storage [10,11,27]. Furthermore, a decrease in the intensity of the band at 1448 cm^{-1} assigned to the CH_2 and CH_3 bending vibration was observed. The latter decrease can be the result of the hydrophobic interactions occurring around the aliphatic residues [10,28]. The results also show an increase in the S-S stretching vibrations (525 cm^{-1}) as recorded by PC1 loadings, which can be attributed to the oxidation of cysteine and methionine amino acid residues [29].

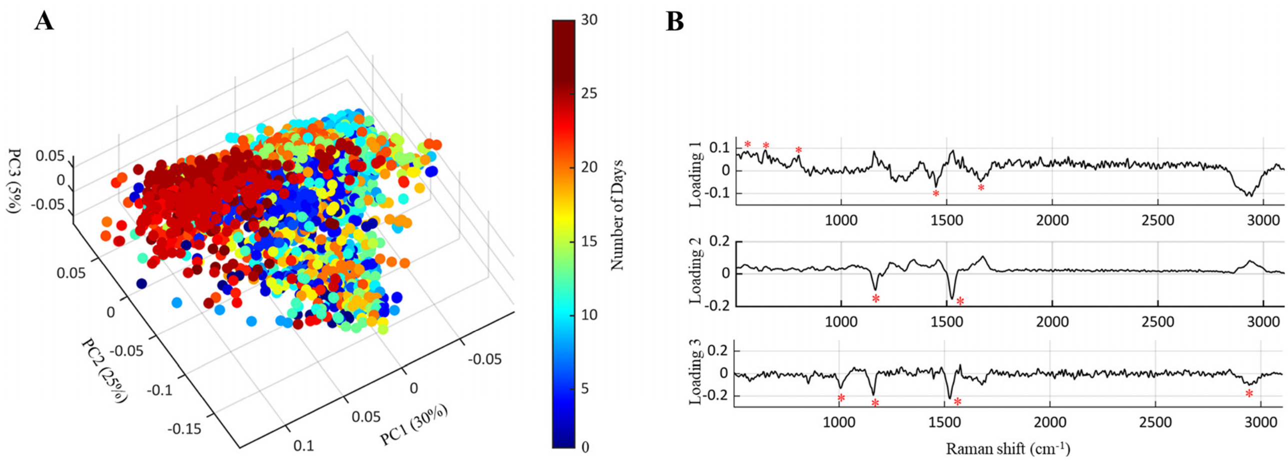

Figure 3. PCA scores (**A**) and loadings (**B**) of chicken breast—Quality overview over 30 days of refrigerated storage (4 °C). (**A**) The scores of the chicken breast spectra of the last ten days (day 21 to day 30) are clearly distinguished from the rest of days where (**B**) the loading plots show the molecules (represented by a red asterisk) impacted during the testing period.

3.2. Application of Raman Spectroscopy, Dealing with Packaged Food

The second stage of testing involved checking the quality of the LDPE-wrapped chicken breast over 30 days. As is known, LDPE has its unique spectrum [30,31], and its Raman bands can be confused with those of chicken bands, as shown in Figure 4. The LDPE spectrum was therefore acquired and compared with the chicken spectrum (Figure 4). Only a few chicken-related bands were visible (Figure 4), which are Amide I (1655 cm^{-1}) and Tyr (845 and 640 cm^{-1}).

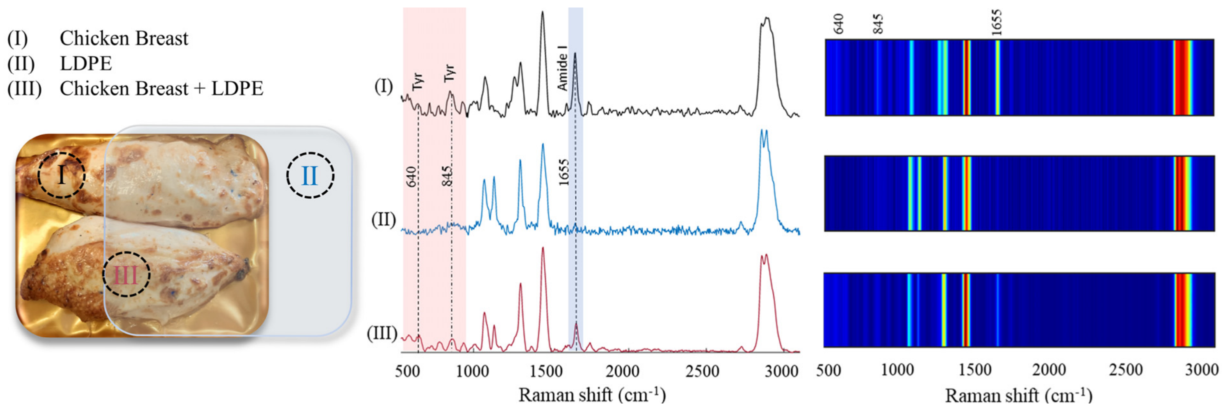

Figure 4. Inspecting the Raman bands of chicken that have no interference with the packaging layer (LDPE). The highlighted regions show two distinct bands: Amide I 1655 cm^{-1}, and Tyrosine (640 and 845 cm^{-1}). (I): Chicken spectra; (II): LDPE spectra; (III): Combined spectra of chicken and LDPE.

Since Amide I and Tyr were the only bands that did not have any interference with LDPE Raman bands, as shown in Figure 4, the effect of these bands on chicken quality was further examined by calculating the area under the curve and correlating the obtained results with PCA scores and loadings. The amide I band is considered an indicator of the total protein concentration [10,11]. Figure 5 shows an inverse relationship between the storage time of chicken fillets and the area under the curve of 1655 cm^{-1} (Amide I). In contrast, Tyr showed a complementary response to storage time, where the peak area increased with time. Additionally, when comparing the first five days of storage with the last five days of storage, there appears to be around a 60% difference in the intensities of both peaks, as shown in Figure 5. We believe that denaturation of Amide I results in the formation of free amino acids, of which Tyr is one of the amino acids detected by Raman spectroscopy. These results are also consistent with those presented previously (Stage I), especially when referring to Amide I and Tyr bands. PCA was also conducted on the Raman data of the LDPE-wrapped chicken breast. Figure 6 shows that PC1 carried the most spectral variances over 30 days, explaining about 87% of the variance. Other PCs (PC2 and PC3) contained about 1% of the variance between samples. PC1 scores show a pattern shifting from left to right, as shown in Figure 6A. It seems that the days with the highest quality (day 00–day 05) have positive scores, shifting towards negative scores until the last five days where the deterioration in quality is the highest. The main contributions for PC1 were from Tyr at 845 and 640 cm^{-1} with a negative sign of loadings, and Amide III and C-H stretching at 1655 cm^{-1} with a positive sign of loadings (Figure 6B). Loadings 2 and 3 did not provide any significant information, as the PC2 and PC3 scores showed negligible variations among the samples.

After establishing the Raman bands responsible for the variation in the quality of chicken wrapped in LDPE, PC1 scores were then subjected to Kruskal Wallis to get an estimate on the day the quality started shifting, and the results are shown in Figure 7A,B. The results show the days on which the portable Raman system was able to detect a change in the chicken's quality. For instance, the first shift in quality was detected on day six, as seen in Figure 7A, where this day seems to separate the samples into two groups as shown in Figure 7B (p-value < 0.05). The same occurs on day 12. However, the biggest shift in PC1 scores was noted after day 21 (Figure 7A), and these results are in accordance with those presented in Figure 5. The total area of Amide I started decreasing from day six, with its highest decrease being recorded on the 30th day.

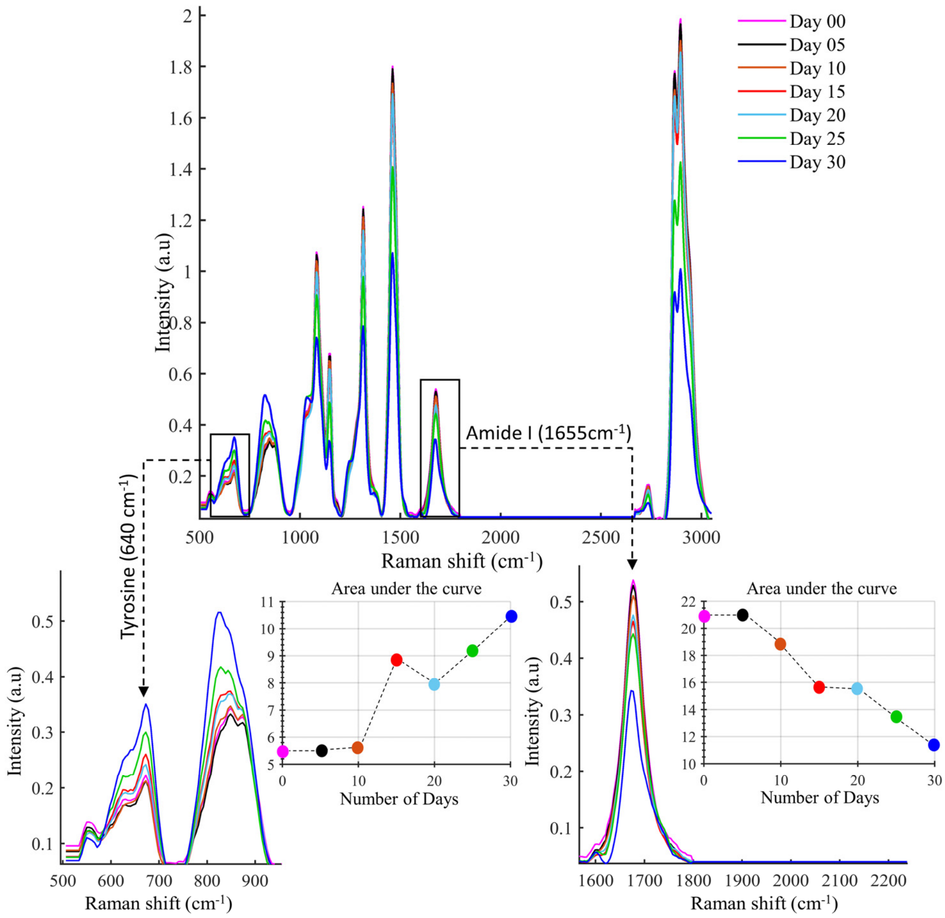

Figure 5. Relation between storage time, intensity and area under the curve of the Raman bands (1655 and 640 cm^{-1}) that had no interference with LDPE. Amide I (1655 cm^{-1}) witnessed a decrease in the intensity and in the area under the curve, whereas Tyrosine (640 cm^{-1}) showed a contrary response as the storage period increased.

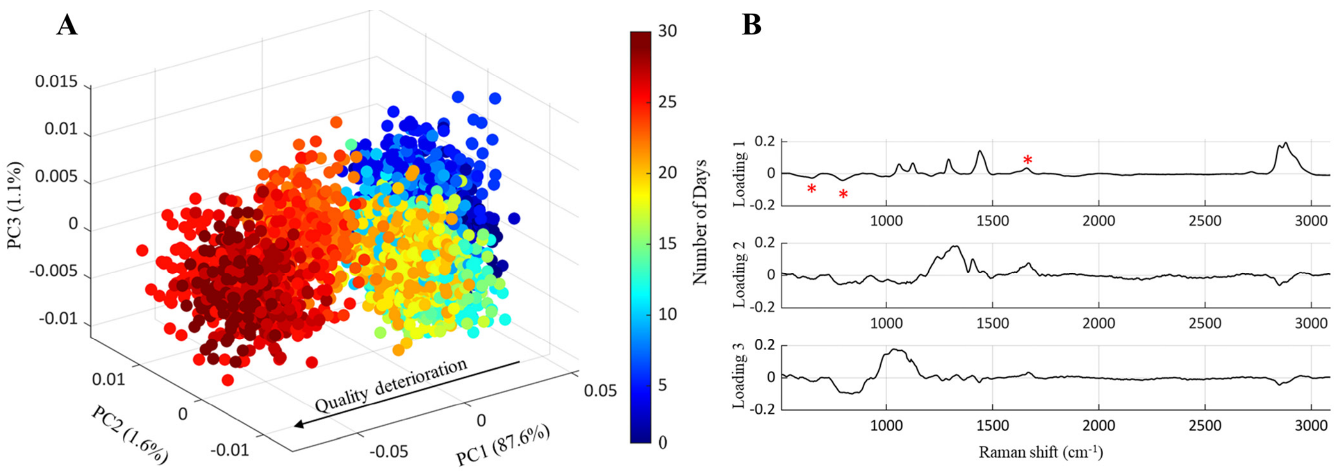

Figure 6. PCA scores (**A**) and loadings (**B**) of LDPE-wrapped chicken breast. Quality overview over 30 days of storage at 4 °C. (**A**) The PC1 scores of the chicken spectra shifted from positive scores (Day 00) toward negative scores (Day 30) as an indicator of quality deterioration. (**B**) shows the molecules impacted (represented by the red asterisk) during deterioration of the chicken quality, especially on loading 1.

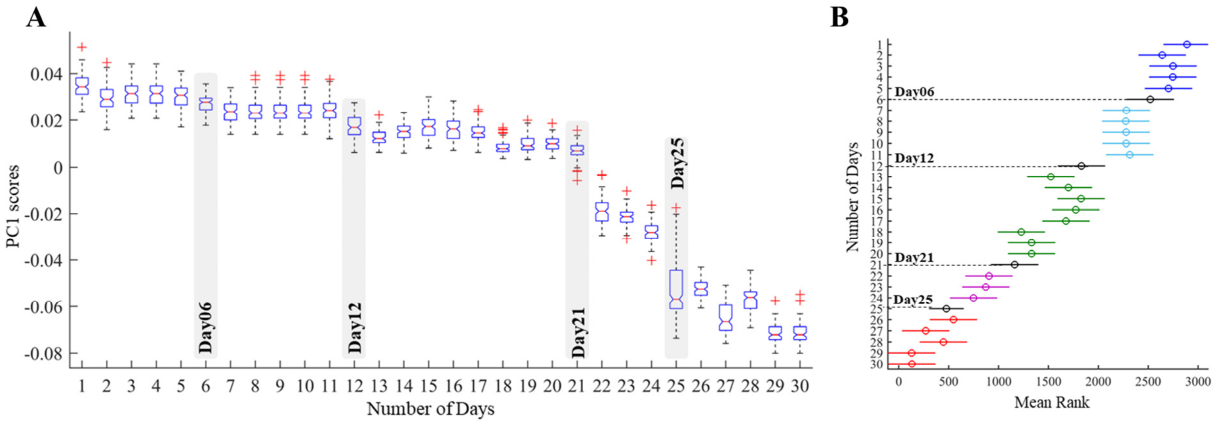

Figure 7. Spotting the days where a shift in the chicken quality is detected by the portable Raman spectroscopy. (**A**) a box plot representing the median of the PC1 scores per day, where the highlighted region shows the day when a shift in quality is detected. (**B**) represents the significant groups separated by the dotted black line. This black line represents the day on which the chicken quality has similarity with the groups before and after.

Based on the results obtained during stage I and stage II, it is evident that Raman spectroscopy can monitor the quality of chicken as it spoils. The results of stage I show the change in protein structure as storage time is increased. For instance, amide I and amide III vibrational intensities decreased, while those of Tyr and S-S stretching increased. These changes in the protein structure indicate that there are several spoilage reactions happening, including microbial growth, denaturation of protein, and oxidation of amino acid residues. Additionally, hydrophobic interaction around the aliphatic residues was noticed through the decrease of the CH_2 and CH_3 intensities.

As for stage II, we can observe that the portable Raman spectroscopy was able to monitor the quality of LDPE-wrapped chicken breast. Even though only two peaks were visible when the product was packaged, Amide I is considered one of the primary protein indicators and, through its denaturation, it is possible to monitor the quality of chicken wrapped in LDPE [10,11]. Most importantly, the system was capable of early detection on the day that the shift in quality started.

The provided results can not only help food industries to monitor product quality but also protect the environment. We believe that showcasing the portable version of the Raman spectrometer holds huge promise in our fight against food waste. This can occur in multiple ways along the food production and distribution chain. For instance, monitoring raw materials at the farm level in real-time using the provided system is quite important, as this can provide farmers with valuable information on the chemical composition of raw materials. This permits farmers to better optimize farm management and to cut foreseeable food losses. This is also achievable at the factory level, where the ability of this portable system to detect changes at the molecular level in seconds can pick up any drastic quality changes in any food item (vegetables, fruits, and meats) and thus rush its production. As for transportation, the portable version of the Raman spectrometer can act as an alert system that can signal the driver to deliver the food products to the nearest food outlet or distribution center in case of a possible food loss. However, for this portable system to be considered as an online application, further investigation and analysis—including sensory testing and examination of the microbes—are required to determine if food products can truly have their shelf life predicted by this method.

3.3. Conclusions

Through the chemometric analysis of Raman spectra, collected by a portable fiber-optic Raman spectrometer, it is possible to monitor the quality of packaged chicken meat in the function of storage time. This system was able to detect the shift in the product's quality, the chemical components impacted during the course of quality deterioration, and the day when the food quality started changing. The capabilities of such a system render it an important contributor to reducing food waste, and its potential is limitless. This is why our future work will focus on increasing the number of tested samples, the use of different food samples, and finally, real-time testing on the road.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15010188/s1, Figure S1: Raman spectra were obtained from 13 different zones with the help of a motorized stage; Figure S2: PC3 scores and loadings—Quality overview over 30 days of refrigerated storage (4 °C).

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Conflicts of Interest: The authors declare no competing financial interest and respect the ethics of references.

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Life Cycle Assessment Tool for Food Supply Chain Environmental Evaluation

Tamíris Pacheco da Costa [1,*], James Gillespie [2], Katarzyna Pelc [3], Abi Adefisan [4], Michael Adefisan [4], Ramakrishnan Ramanathan [5] and Fionnuala Murphy [1]

1 School of Biosystems & Food Engineering, University College Dublin, Agriculture Building, UCD Belfield, D04 V1W8 Dublin, Ireland
2 School of Computing, Engineering and Intelligent Systems, Magee Campus, Ulster University, Northland Road, Londonderry BT48 7JL, UK
3 Bedfordshire Business School, University of Bedfordshire, Putteridge Bury, R. 220, Hitchin Road, Luton LU2 8LE, UK
4 Yumchop Foods, Westward, Brackley Road, Towcester NN12 6HX, UK
5 Essex Business School, University of Essex, Southend Campus, Elmer Approach, Southend-on-Sea, Essex CO4 3SQ, UK
* Correspondence: tamiris.dacosta@ucd.ie

Abstract: Food is at the centre of efforts to combat climate change, reduce water stress, pollution, and conserve the world's wildlife. Assessing the environmental performance of food companies is essential to provide a comprehensive view of the production processes and gain insight into improvement options, but such a tool is currently non-existent in the literature. This study proposed a tool based on the life cycle assessment methodology focused on six stages of the food chain, raw materials acquisition, supplier, manufacturing, distribution, retail and wastes. The user can also evaluate the implementation of Internet of Things (IoT) technologies to reduce food waste applied in the real-world problems. The tool was validated through a case study of a food manufacturing company that prepares frozen meals via vending machines. The LCA results provided by the tool showed that food raw materials production is the main hotspot of nine impact categories. The IoT technologies' contribution increased the company's impact by around 0.4%. However, it is expected that employing these monitoring technologies would prevent food waste generation and the associated environmental impacts. Therefore, the results of this paper provide evidence that the proposed tool is suitable for determining environmental impacts and savings of food supply chain companies.

Keywords: environmental analysis; food supply chain; IoT technologies; life cycle assessment; excel-based tool; stand-alone model

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1. Introduction

Around 10% of food made available to EU consumers (at retail, food services and households) may be wasted [1]. These losses occurred at different stages of the food supply chain (FSC), i.e., in companies converting the raw agricultural materials into final products feasible for direct consumption [2]. Literature suggests that issues within FSC management leading to food waste are numerous, including inadequate processing and packaging, lack of transportation and distribution systems and inadequate storage facilities and techniques [3,4], and call for targeted action.

In particular, in the EU, nearly 57 million tonnes of food waste (127 kg/inhabitant) are generated annually, with an associated market value estimated at 130 billion euros [1]. By preventing food waste, companies can sell more food and create more revenue. However, the importance of reducing food waste has been recognised worldwide not only because food waste causes serious economic impacts but also due to environmental and social consequences [5]. Due to the amount of resources (water, nutrients, fertilisers, etc.) consumed during food production and distribution, food waste saved is much more than the face value of the waste itself for society [6]. Regarding environmental effects, the food sector accounts for over 30% of global greenhouse gas (GHG) emissions [2]. Significant carbon emissions result from the production of food that is wasted, and the wasted food will emit more GHG in landfill, causing significant environmental impacts. To reduce carbon emissions, various companies have been seeking ways to reduce their own emissions [7].

Recent research supports the importance of using smart technology such as the Internet of Things (IoT), machine learning and blockchain to advance and improve FSC management [5,8–12] and thus help reduce food waste. The IoT is a growing network of objects that communicate between themselves and other internet-enabled devices over the Internet and allows users to monitor and control the physical world remotely [13]. In the supply chain context, Abdel-Basset et al. [14] defined IoT as a set of digitally connected physical objects for sensing and monitoring supply chain interaction, agility, visibility and information sharing to facilitate the plan, control, and coordination of supply chain processes within an organisation. In addition, adopting IoT is a potential opportunity to upgrade and reshape the FSC [12], and help data-driven decision-making in supply chain management [15].

Several areas in the field of IoT implementation in the FSC were discussed in the literature, including implementation models and frameworks [16–18], managing risks and revenues [9,19], platform design [16], usefulness [20], supply chain sustainability [21], supply chain coordination and information sharing [19]. Even though IoT and FSC applications were discussed in the literature, there is a lack of studies on tools assessing the environmental performance of different food products, food supply chain stages and technologies used to reduce food waste in FSC [22].

Life cycle assessment (LCA) is a methodology that can analyse the environmental impacts of products or processes by inventorying all the inputs and outputs throughout the product's life cycle, from raw material production to end-of-life [23–25]. This methodology determines where the most significant impacts occur and where the most relevant improvements can be made while identifying potential trade-offs [26,27]. It allows companies to investigate areas where they might improve [28,29]. Although some LCA tools exist for other sectors [30–32], there is no generalised LCA tool for understanding the environmental impacts of different stages of the food supply chain or implementing IoT technologies to save food waste. Such a tool will be invaluable given the increasing trend in the food industry for using new technologies. This paper fills this gap and contributes to the literature.

Therefore, this study aims to develop a new adaptable open-source tool (REAMIT-LCA Tool) to conduct an extensive environmental evaluation of food supply chains. The tool is used to compute the contribution of each stage of the food supply chain to 12 different impact categories to support food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers in conducting LCA and exploring the problem of food waste and the solutions to achieve more sustainable food systems. It can also be used as an environmental decision support system to determine the trade-offs between IoT technologies implementation and food waste reduction. Additionally, developing a complete LCA can be difficult and time-consuming, particularly discouraging to non-experts. Therefore, it also aims to reduce the computational time and processing, which the other LCA tools have not yet resolved.

The paper is organised as follows. A literature review of LCA tools is shown in the next section. The REAMIT-LCA tool scope is discussed in Section 3, along with the modelling methods, data sources and validation in a UK food manufacturing company case study. Results are presented and discussed in Section 4. Additional sensitivity analyses are also performed in this section. Conclusions are shown in the Section 5.

2. Literature Review

In recent years, various computational tools were developed to assess the environmental impacts of different products and organisations from an LCA point of view. Table 1 presents some examples of tools proposed in the literature. It is not intended to be a comprehensive list of all available tools and/or methodologies proposed but only to present some of the most representative tools that can be used in practice.

Table 1. LCA tools available to assess the environmental impact of different products.

Authors	Year	Application	System Boundary	Geographical Coverage	LCI Database	Modelling Approach	Indicators	Analysis Tool
Hassan et al. [33]	2022	Residential building	Gate-to-gate (excludes transportation and other life cycle stages)	Egypt	Ecoinvent	ReCiPe and IPCC 2013	GW, DEQ, HH, RM	Excel
Kamari et al. [34]	2022	Building design	Cradle-to-grave (from materials production to building's end-of-life)	-	OKOBAUDAT platform	IMPACT 2002+	GW, OD, POF, AD, EU, AC	Plug-in icon in the Autodesk Revit software
Hollberg et al. [35]	2022	Building	Cradle-to-gate (from materials production to transportation)	Sweden	Boverket	IPCC 2013	GW	Grasshopper3D used as platform for the tool
Famiglietti et al. [36]	2022	Cities	Cradle-to-grave (from materials production to end-of-life stage)	-	-	EF 3.0	All categories of the EF method	Excel
Famiglietti et al. [37]	2019	Dairy products	Cradle-to-gate (from purchased feeds to dairy production)	-	Agribalyse, Ecoinvent, ELCD, USLCI, etc.	ILCD 2011 Midpoint +	All categories of the ILCD 2011 method	IT-tool
Tecchio et al. [38]	2019	Building structure	Gate-to-gate (material production stage only)	USA	Ecoinvent, USLCI, Athena, GaBi	-	GW, AC, EU, SF	Box plots
Hasik et al. [39]	2019	Office buildings	Cradle-to-gate (from materials production to building stage)	USA	Ecoinvent	-	GW, OD, SF, AC, EU, FD	Python
Hester et al. [40]	2018	Residential buildings	Cradle-to-grave (from materials production to building's end-of-life)	USA	Ecoinvent, GaBi, Athena, etc.	-	GW	Excel
Martins et al. [41]	2018	Electricity	Cradle-to-gate (from extraction of raw materials to final decommissioning)	Portugal	IPCC Emission Factors	CML	GW, OD, POF, EU, AC	Excel
Renouf et al. [42]	2018	Sugarcane	Cradle-to-gate (from farming inputs production to sugarcane harvesting)	Australia	AusLCI	CML, IPCC 2013, USEtox	GW, FD, EU, WS, EC	Excel
Goglio et al. [43]	2018	Soil emission	Cradle-to-gate (from agricultural phase to products transportation)	Canada	GHGenius	IPCC 2013, and CML	GW, CED, EU, AC	Open-source program R

Table 1. *Cont.*

Authors	Year	Application	System Boundary	Geographical Coverage	LCI Database	Modelling Approach	Indicators	Analysis Tool
Yang et al. [44]	2017	Airport pavement construction	Cradle-to-gate (from materials production to construction)	USA	Ecoinvent	-	GW, CED	Excel
Beccali et al. [45]	2016	Solar heating and cooling systems	Cradle-to-gate (from production of the main components to end-of-life)	23 European countries, Switzerland and Europe	-	Frischknecht and Rebitzer [46] and IPCC 2013	GW, CED	Excel
Al-Ansari et al. [47]	2015	Agri-food production	Gate-to-gate (food production)	Qatar	-	CML	GW, AC, HT, AD, AE, LF	-
Basbagill et al. [48]	2014	Residential complex	Cradle-to-gate (from materials production to building stage)	USA	Ecoinvent, Athena	-	GW, cost	ModelCenter software
El-Houjeiri et al. [49]	2013	Crude oil production	Well-to-refinery	All countries except Cameroon, Chile, South Africa, and Uzbekistan	Different databases	-	GW	Excel
Mata et al. [50]	2012	Pharmaceutical products	Gate-to-gate (from raw materials transportation to post-consumer)	-	-	CML	EI, PMI, PW, CF, FT	Excel
Reinhard et al. [51]	2011	Biofuels	Cradle-to-grave (from cultivation to usage)	-	Ecoinvent	IPCC 2006	GW	Web-based tool
Current study	2022	Food products	Cradle-to-grave (from materials production to waste end-of-life)	Ireland, Germany, France, Luxembourg, UK and the Netherlands	Ecoinvent [52,53]	ReCiPe	GW, FS, SOD, TA, TEc, LU, MEu, MEc, HT, FEu, FEc, WC	Excel

Acidification potential (AC), abiotic depletion (AD), aquatic ecotoxic (AE), cumulative energy demand (CED), carbon footprint (CF), damage to ecosystem quality (DEQ), ecotoxicity potential (EC), energy intensity (EI), eutrophication potential (EU), fossil fuel depletion (FD), freshwater ecotoxicity (FEc), freshwater eutrophication (FEu), freshwater aquatic toxicity (FT), fossil resource scarcity (FS), global warming (GW), human health (HH), human toxicity (HT), land footprint (LF), land use (LU), marine ecotoxicity (MEc), marine eutrophication (MEu), ozone depletion (OD), photochemical ozone formation (POF), process material intensity (PMI), process water (PW), resources metrics (RM), smog formation (SF), stratospheric ozone depletion (SOD), terrestrial acidification (TA), terrestrial ecotoxicity (TEc), water consumption (WC), water scarcity (WS).

It was observed that most of the tools are excel-based. Most of them only calculate the global warming potential. The focus on this category is understandable, as it is considered one of the most critical indicators, and most strategies and/or policies to mitigate the effects of climate are based on it, as the goals are expressed in terms of reduction in carbon emissions. Yet, other indicators are relevant, and some tools are being developed to address them, such as tools proposed by Famiglietti et al. [36] and Famiglietti et al. [37]. Some available tools are also starting to include other tools and methodologies, such as the LCA and economic evaluation proposed by Basbagill et al. [48]. Data sources vary and include emission factors recommended by international organisations such as the Ecoinvent database and the IPCC Emission Factors Database. Additionally, some tools use regional or country-specific data, limiting their applicability when used in other geographic areas.

Despite a protracted theoretical discussion on the simplification of LCA, few approaches and tools have been developed and proposed for the agri-food sector. Food products are not part of the scope of a significant part of the tools found in the literature, which are focused on the building [33–35,38] and energy [41,49,51] sectors. Only a few tools have been developed to conduct LCAs in agriculture [42,47]. Renouf et al. [42] developed a tool and framework to assess the impacts of sugarcane-growing practice alternatives. Briefly, this LCA tool focuses on 'cradle to farm gate' operations from farming inputs production to sugarcane harvesting and relevant impact categories, such as global warming, fossil depletion, eutrophication potential, water scarcity, etc. To validate the tool, the authors assessed a case study of actual practice changes in the Wet Tropics region of Australia. The results generated by this tool were consistent with those generated by past studies using LCA software. Al-Ansari et al. [47] created an integrated energy, water and food life cycle assessment tool to provide an environmental assessment of food production systems. However, the system boundary of this system is limited to the food production phase. As observed, these tools are either simple tools or have a limited scope.

Integrating agri-food processes within the incorporated databases of simplified LCA tools can be of fundamental importance for the agri-food products case studies. The REAMIT-LCA tool is publicly available online, has a user-friendly framework and can run in Microsoft Excel. Unlike previous tools developed for LCA, the REAMIT-LCA tool includes other impact categories besides global warming, such as fossil scarcity, land use, human toxicity and water consumption. Furthermore, it was developed in compliance with International Standard Organization's (ISO) 14040/14044 guidelines [52,53], applies characterisation factors from the ReCiPe method, focuses on different stages of the food supply chain and can be applied in different countries of North West Europe.

3. Methodology

3.1. The REAMIT-LCA Tool

This tool has been developed based on the work performed in the REAMIT project. This project was launched to support food companies in North-West Europe (NWE) to reduce food waste by applying existing innovative technologies, such as the Internet of Things (IoT) and Big Data [54]. IoT technologies have been identified as a potential breakthrough class of technologies to reduce food waste this decade [55–57]. Through testing and adaptation, these technologies enabled the continuous monitoring and recording of food quality and potential issues [8,58]. Through analytics, owners of 'food to be at risk of becoming waste' are provided with decision support options to minimise food waste, including redistribution to nearby customers [59,60]. The project focused on fruits, vegetables, meat and fish, which are wasted in large quantities. The supply chain included farms, packaging sites, food processors, distribution, logistics, wholesalers and retailers. The project was carried out in Ireland, Germany, France, Luxembourg, the UK and the Netherlands due to the interconnected food supply chains and massive food waste in these countries [54].

The REAMIT project observed that there was demand among its partners, food product manufacturers, for a tool providing insight into the environmental performance of their products. This demand arose from a desire to improve the environmental profile of products across the product chain. The food supply chain is a very diverse sector comprising manufacturers specialised in a wide range of complex food products [61,62]. In many cases, the results of existing generic LCAs tools cannot be translated into the food supply chain practice [22]. Therefore, it was essential for the tool to be adaptable, allowing the users to model and analyse their specific product system. The tool, which was named the REAMIT-LCA tool, was developed as a joint venture by researchers from a variety of organisations and food companies and is available to companies without fees.

It contains LCA information on the processes in each phase of the food production chain and provides a life cycle framework to help evaluate diverse categories of food products in a consistent manner. The user constructs a product's life cycle by selecting the relevant food materials and, subsequently, the appropriate production process(es) per life cycle phase. The tool focuses on 12 different impact categories to offer a comprehensive view of the potential environmental impacts of the organisation under analysis. With the tool, the company can gain insight into its products' life cycles and the contribution of company-specific production processes within the entire life cycle. It can also be used to develop strategies to reduce the environmental impacts associated with food waste production and for food companies to evaluate their processes and make necessary improvements at an early stage of development.

The REAMIT-LCA tool is a spreadsheet-based, stand-alone model operating in Microsoft Excel through which the user can navigate, and it is compatible with both PC and Mac versions of Excel. The tool is available in the Supplementary Material. Before starting, for security reasons, the "Trust Center" settings in Microsoft Excel must be set to allow needed Visual Basic for Applications (VBA) code to execute. Click the "Enable Content" button next to the security warning message to open the tool's main Menu dialogue box. The tool is organised in separate sheets where users can check and adjust the data to fit their own processes. It follows the four phases of the LCA methodology, according to ISO 14040/14044 [52,53]. The LCA tool's general structure, including the life cycle stages of the food supply chain, can be seen in Figure 1. The methodological framework and the Excel-based tool will be described in the sections below.

3.1.1. Goal and Scope

The tool is recommended for food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers to explore the problem of food waste and the solutions to achieve more sustainable food systems. In addition, it captures the entire food supply chain (from cradle-to-grave) and contains information on a wide range of materials, production processes of various food manufacturing phases, packaging materials, end-of-life treatments and transportation modes. The user can construct the entire life cycle by selecting the appropriate processes per life cycle stage. The life cycle stages considered by the tool are shown in Figure 2.

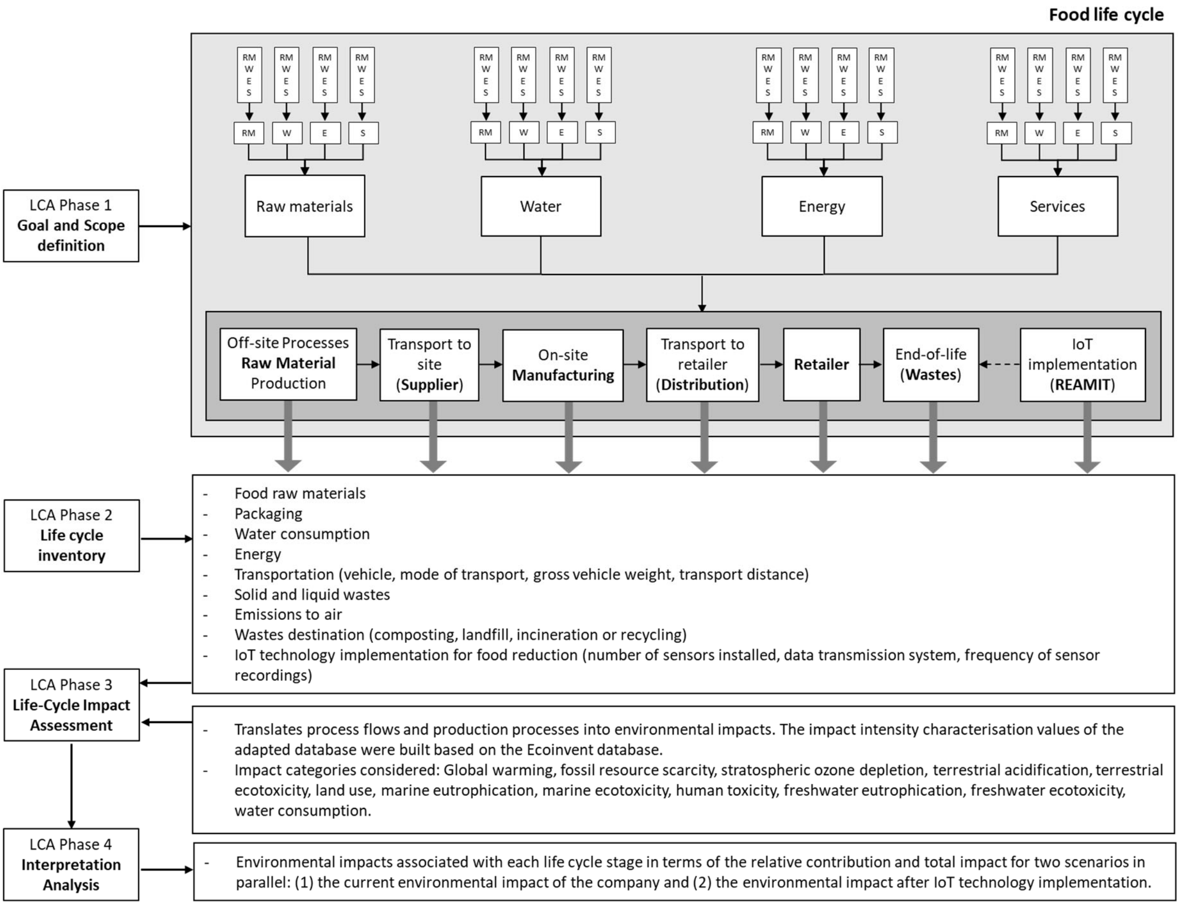

Figure 1. General structure of the LCA tool, including the life cycle stages of the food supply chain.

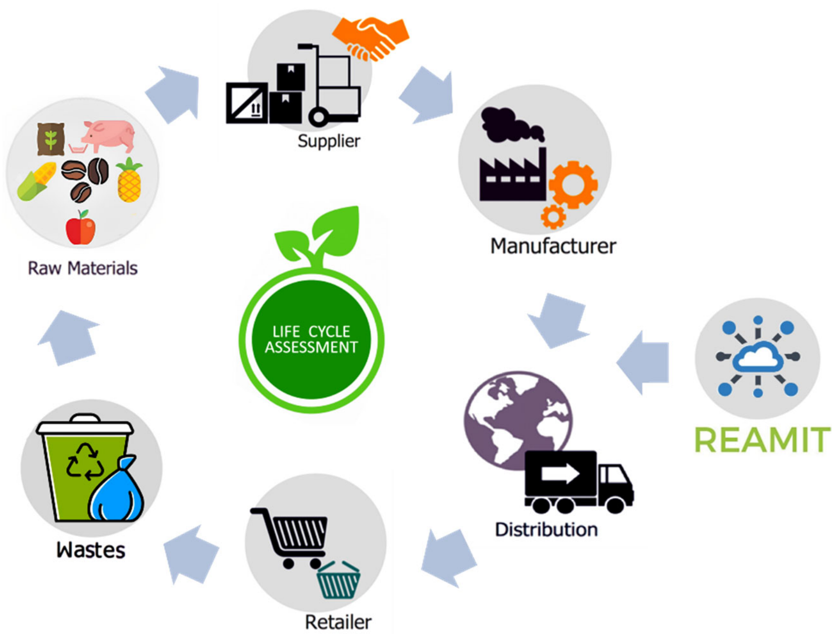

Figure 2. Life-cycle stages considered in the REAMIT-LCA tool.

The system boundary encompasses seven stages: raw materials, supplier, manufacturing, distribution, retail, wastes and REAMIT technology. The raw material's general scope includes acquiring an initial set of food products. More than 60 food products were included in the tool database and were organised into four categories: (i) cereals, leguminous crops and oil seeds, (ii) vegetables, roots and tubers, (iii) fruits, and (iv) animal products. The supplier stage includes raw materials transportation from the supplier to the food company under analysis. It allows the user to select between different types of vehicles, modes of transport and gross weight.

In the manufacturing stage, it is possible to include some inputs from the food manufacturing process, such as water consumption, energy (including electricity and fuels), and packaging materials. Some output emissions to air and water are also included in this stage. Solid waste generation, including packaging materials and food waste, were organised in a specific stage. The distribution consists of product transportation from the food company to retail. The inputs included in the retail consist of energy consumed during food storage.

The tool is general and should be adapted to each food company, i.e., each company can fill the stages present in their life cycle and disregard the unnecessary stages. The functional unit of the reporting results will refer to the amount and nature of food products provided by the food company over the reporting interval. In this case, the functional unit is the sum of all products included in the distribution stage and allocation between products is not available in this tool. The reporting interval is recommended to be one operation cycle of the food company, i.e., one year is the preferred option.

In the tool, the goal and scope worksheets include: (1) the menu with the links for all the stages of the food chain that can be analysed using this tool and (2) a more information worksheet that provides the author list, a brief user guide containing the purpose of the project and some specifications of the tool, the terms of use and a tutorial video.

3.1.2. Life Cycle Inventory

The food supply chain life cycle inventory worksheets include all essential inputs and outputs that need to be filled to run the tool and generate results. General and pathway-specific assumptions may be changed on this worksheet. Since the REAMIT-LCA tool is designed for food companies, users can either complete the product's entire life cycle (seven stages) or investigate one specific production phase (e.g., distribution).

Users start selecting the food raw material item of interest and the appropriate weight. By changing the values of consumption, the figures on the results worksheets will update automatically. The tool does not calculate any material quantities. The user should perform calculations before modelling the food materials in the tool. It should be noted that quality data is crucial in the life cycle assessment methodology. In this sense, the highest possible level of detail is required. In addition, the user should document any assumptions that go into the calculations.

If the user intends to evaluate the transportation performance in the distribution stage, additional information should be provided using the drop-down lists included in the tool. In this stage, the user must select the appropriate transportation specifications under three forms—train, ship, and road vehicle (lorry). In addition, the transportation distances (in km between origin and destination) associated with the food materials used by the company should be provided, as well as the mode of transport (freezing, cooling, or none) and, if applicable, gross lorry weight.

In the manufacturing stage, all inputs consumed for food production must be added, including consumption of water, energy and packaging materials. Some inputs have regionalised characterisation factors, such as electricity consumption; therefore, the user must select in which country the consumption is made. Data selected for inclusion in the tool reflect national averages and do not reflect regional variation in practice. A list of outputs that may occur during the manufacturing step is also provided, such as emissions to air and water. Solid waste was organised in a different worksheet, including all solid waste produced in the previous stages. In this stage, it is necessary to define the final destination of each solid waste using the drop-down menu, for example, composting, landfill, incineration or recycling. Some final destination options are limited to specific scenarios due to database limitations.

The REAMIT stage is treated as a sensitivity analysis case of the LCA methodology, where temperature and humidity sensors and a Big Data server are hypothetically implemented in the company to monitor food quality and prevent its degradation along the supply chain. In this stage, it is possible to simulate the incorporation of temperature sensors in the company's system, selecting the number of sensors planned, the data transmission system (GSM-based or LoRa) and the frequency of sensor recordings per hour, which will influence the amount of data stored in the Big Data cloud server and consequently the electricity allocation. Credit is given to the system for avoiding additional food production to cover the losses and all related upstream activities avoided, according to the amount and type of food avoided.

The sensors considered in the REAMIT-LCA tool are composed of a printed circuit board (PCB), flexible copper cables, a temperature/humidity probe, lithium batteries, stainless steel screws and a housing top and bottom made with plastic. Installation of the sensor is performed manually, and no environmental burden was assumed. The life span of the sensor considered in this study is 10 years [63]. The sensors transmit the temperature/humidity information to a Big Data Server, and the user can select the mode of transmission, i.e., via a GSM-based (4G) or LoRa network. In this study, sensors operating through a GSM-based mode are composed of four lithium batteries that provide energy to support temperature/humidity analysis and data transmission. Therefore, no other electricity or power is required during the use phase of this type of sensor. According to the supplier, the batteries last about 4 years, considering one recording every 20 min. However, the field testing showed that the lifetime is 87% lower. The complete inventory data of raw materials, manufacturing, use, and end-of-life were described in da Costa et al. [64].

On the other hand, sensors operating through a LoRa network have a lower power consumption and require only two batteries. According to the supplier, LoRa sensors batteries last around 4–6 years, considering one measurement every 20 min. In this case, additional digital technology is required to transmit the data to the Big Data Server, as many countries still do not have a countrywide LoRa network. Therefore, it is necessary to integrate a gateway connecting two networks with different transmission protocols. In this scenario, it was considered that the gateway operates 24 h per day and has a power consumption of 7W. The only exception is the sensor that operates in the Netherlands, as KPN deploys the LoRa IoT network across this country and sensors work without an additional gateway.

The data is transmitted to the server, and alerts are sent when the temperature exceeds an acceptable limit. This alert helps the company fix any malfunctioning of the fridge/freezer before the stored items go to waste due to temperature fluctuations. The Big Data Server comprises one unit of computer equipment, a redundant power supply, processors and storage drives with a total capacity of 3.7 TB. The estimated electricity consumption of the server is 1152 kWh per month. To allocate the electricity consumption, it was considered that each row of data generated per recording occupies around 87 bytes in the server.

The database worksheet contains a list of materials used in the food supply chain (e.g., food products, packaging, water, fuels, electricity, etc.) and associated characterisation factors used to perform the environmental impact estimation, as well as a list with acronyms. The inventory data of raw materials production, water, energy and emissions due to transportation were taken from the Ecoinvent database [65]. Environmental impact data are specified for the unit database items. Therefore, the user cannot edit or delete default database items in this worksheet since it may affect the reference and the code in the model's background. For each input and output, there is a specific cell with calculations in the worksheet life cycle impact assessment (LCIA); the methodology will be explained in the section below.

3.1.3. Life Cycle Impact Assessment Methodology Applied in the Tool

This section provides a summary of the LCIA methodology structure to give the user a quick overview of the model's main features used in the REAMIT-LCA tool. It follows the computational structure of the life cycle assessment proposed by Heijungs and Sangwon [66]. In short, the LCA principle can be presented with three matrix equations. Equation (1) is used to translate process data into a production system.

$$s = A^{-1} \cdot f \tag{1}$$

where s is the scaling vector which describes the necessary intensity of production processes, A is the database of process flows and production processes, and f is the final demand vector or the output desired from the system. The scaling vector calculated from the first equation is used to determine the intensity of emissions from unit processes (Equation (2)).

$$g = B \cdot s \tag{2}$$

where g is the emission inventory vector describing the emissions caused by the whole system, and B is the unit emission matrix (a database of process values).

Equation (3) translates emissions into environmental impacts (e.g., CO_2 emissions into climate warming potential).

$$h = Q \cdot g \tag{3}$$

where h is a vector representing the environmental impacts caused by the system and Q is a characterisation matrix (a database of impact intensity characterisation values).

The model follows the International Standard Organization's (ISO) 14040/14044 guidelines [52,53]. The characterisation factors and the impact categories used in this tool are those of the ReCiPe method at the midpoint level following a hierarchical perspective [67]. The following environmental impact categories were included in the tool: Global warming (GW), fossil resource scarcity (FS), stratospheric ozone depletion (SOD), terrestrial acidification (TA), terrestrial ecotoxicity (TEc), land use (LU), marine eutrophication (MEu), marine ecotoxicity (MEc), human toxicity (HT), freshwater eutrophication (FEu), freshwater ecotoxicity (FEc), water consumption (WC).

3.1.4. Interpretation

Having filled the inventory of relevant processes in the previous sections, the user can view the environmental results on the LCA results worksheet by clicking the "Next" button available in the top right corner of the tool. The charts built in this worksheet show the environmental impacts associated with each life cycle stage (raw materials, supplier, manufacturing, distribution, retail, wastes) for two scenarios in parallel: (1) the current environmental impact of the company and (2) the environmental impact after IoT technology implementation (REAMIT strategy). Results are shown for the 12 impact categories in terms of the relative contribution of each stage of the supply chain (Figure 3), while a table shows the absolute values of each impact category results per stage.

These graphs can support the user in visualise the life cycle stages that substantially influence the overall environmental impact of the organisation under consideration. To better comprehend the causes behind the environmental impacts, the user can explore the details of the numerous process contained in those life cycle stages, which can then be used to identify viable solutions to reduce those impacts. The user can find further explanations about how to interpret LCA findings in Zampori et al. [68]. To select and copy an existing graph in the results, click the "Copy" button and then click the "Paste" button in another document. Save the file and exit the tool.

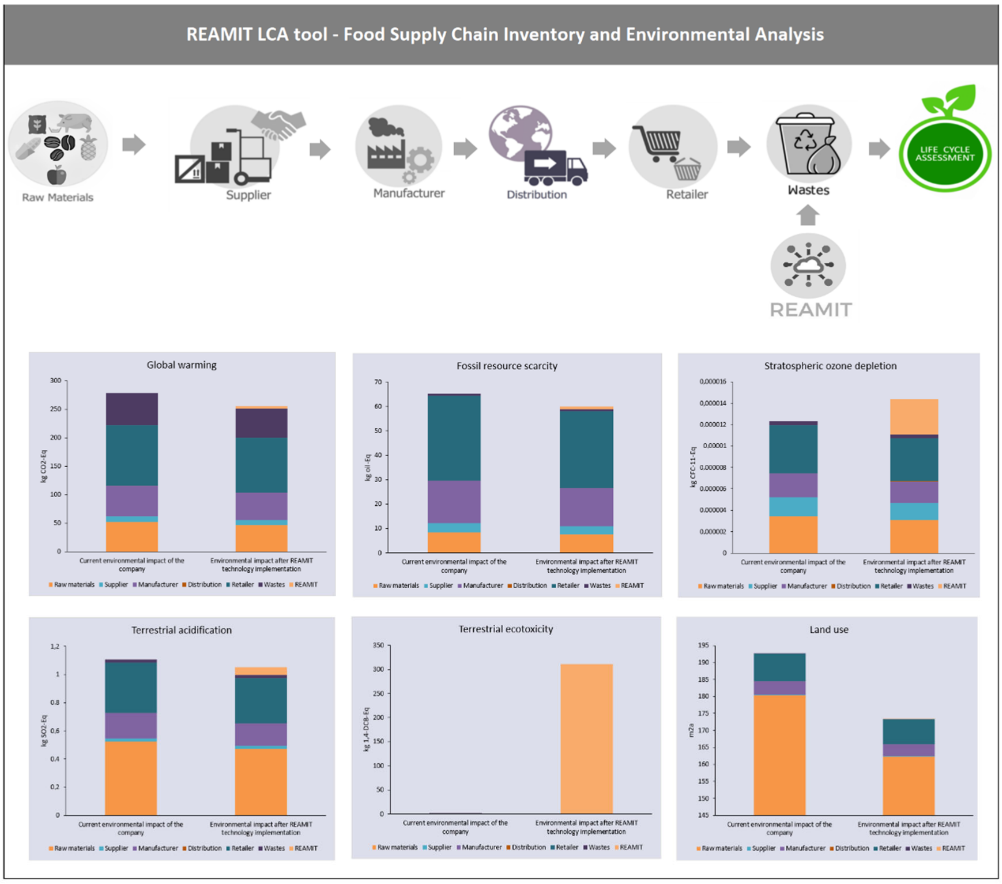

Figure 3. Example of results given by the REAMIT LCA tool.

3.1.5. Tool Assumptions and Limitations

The use of results is designed to provide insight into the life cycle of a company's food products, as well as the contribution of company-specific production stages within the entire life cycle. It can also be used for assessing the environmental impacts of improvement options. However, caution should be taken when interpreting the LCA results. To use the REAMIT-LCA tool, knowledge about the manufacturing phases of food products and LCA interpretation is recommended. The user is responsible for the selection of the appropriate inputs and outputs. The tool does not check data quality. The user is responsible for reviewing the completeness, consistency, and accuracy of the data related to all items (type of food products, quantity, etc) used in the analysis.

In addition, the tool is built assuming that each alternative's functional unit is the same. The definitions of the functional units or the alternatives should be equivalent if the study's objective is to compare alternatives. When comparing different options, it is the user's responsibility to choose the proper functional unit. In addition, the tool does not check for improper comparisons or does not provide warning message notices. The tool will still present the results for any analyses the user sets up, but the results may be unreliable or inaccurate. Therefore, it is the user's onus to make sure that the proper comparisons are made.

The tool supports only specific measurement units, mainly from the International System of Units. If the units the user needs to include are different from what the tool can handle, the user must convert them to the ones compatible with the tool before entering the data. For example, pounds (lbs) are not supported by the tool. The user would need to convert that to other units of mass compatible with the tool (e.g., kilogram) before adding the data.

Avoided impacts due to food waste reduction were modelled in the tool through the system expansion by substitution [69]. Credit was given for avoiding additional food production and all related upstream activities, such as collection, transport and energy required to store the food. However, time frame mismatch was not considered, so avoided emissions estimates must be interpreted cautiously. In addition, the consumption phase is not included in the system boundaries nor the impacts due to infrastructure establishment.

3.2. Validation: Case Study of Food Manufacturing in the UK

3.2.1. Definition of Goal and Scope

The goal of the assessment is to assess the potential environmental impacts of a food manufacturing company located in the UK that prepares frozen food meals for customers via vending machines in which microwave ovens are integrated for heating the food. This innovative hot-cooked food business creates meals that combine multi-cultural traditions, responsibly sourced ingredients free from added preservatives, colouring or flavourings, and packaged in environmentally friendly recyclable and biodegradable packaging. The study focuses on one facility where the entire operations occur.

The functional unit was defined as the total production of frozen food meals during one year of operation, i.e., 9900 kg of frozen food boxes, between January and December of 2021 (reference period). Two scenarios were built to determine the potential environmental savings due to the implementation of a monitoring system based on IoT technologies. Scenario A represents the baseline and includes the processes associated with the food company. Scenario B follows the same processes as scenario A but includes the IoT technologies used to monitor the food quality conditions in the cold storage process during manufacturing.

The system boundaries are illustrated in Figure 4 and follow a cradle-to-grave approach. The processes include raw materials acquisition from the supplier and transportation to the factory, manufacturing (vegetable, meat, poultry and dry ingredients preparation, cooking, finish goods and storage), distribution, retail and solid wastes treatment. Scenario B also comprises digital sensors for measuring the specific parameters, the Big Data server and the food waste avoided. Both scenarios exclude food raw materials production and consumption.

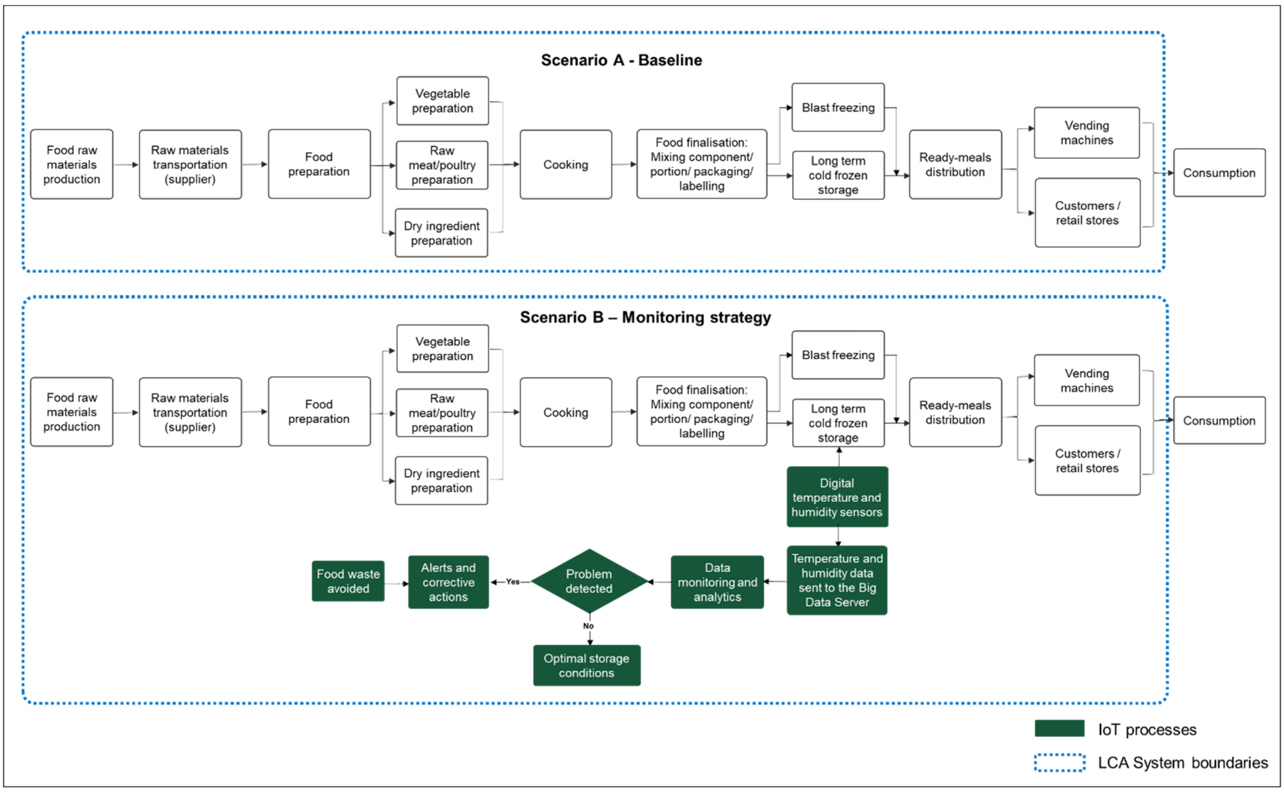

Figure 4. Schematic representation of the system boundaries. (**A**) refers to the baseline scenario, and (**B**) refers to the IoT monitoring strategy implementation.

3.2.2. Life Cycle Inventory

The direct activities data was collected through company interviews. The company uses locally sourced raw materials (vegetables and meat) to prepare their ready-meal products. Fresh vegetables (beans, pepper, etc.) are usually purchased from suppliers located within a radius of 100 km. The vegetables are manually washed, diced, and immediately frozen in blast freezers for 3 h. After the blast-freezing stage, the vegetables are stored in a chest freezer. Rice and other dry foods are stored in the dry room.

Meat (chicken and sheep) is purchased from local suppliers located 30–50 km from the factory. It was considered the average distance (mean: 40 km) for calculation purposes. The meat is transported fresh in temperature-controlled vehicles and stored in fridge storage as soon as it arrives at the production site. The meat is left marinating with oil and spices for two days in the fridge before cooking. Once the food is cooked, it is transferred into a blast freezer to refrigerate the meals for approximately 3 h. The food is weighed and manually packaged in paper boxes of 330 g each. After this process, the boxes are transferred to long-term storage in a cold room with temperatures from −18 to −24 °C. Although cooking is a straightforward method, it involves some waste, nearly 8–10%. For modelling purposes, it was assumed that the food waste would be sent to a municipal sanitary landfill for further management.

The food can be delivered directly to the consumer's home (online shopping) or sent to vending kiosks. The boxes are transported frozen over an average distance of 100 km in refrigerated lorries. Table 2 presents the transportation profile of the company under analysis.

Table 2. Food company transport profile.

Food Group	Inputs	Unit	Transport Distance	Vehicle	Mode of Transport	Gross Lorry Weight
Cereals, leguminous crops and oil seeds	Bean	km	100	Lorry	None	3.5–7.5 t
	Rice	km	100	Lorry	None	3.5–7.5 t
Vegetables, roots and tubers	Pepper	km	100	Lorry	None	3.5–7.5 t
Animal production	Chicken	km	40	Lorry	Freezing	3.5–7.5 t
	Sheep	km	40	Lorry	Freezing	3.5–7.5 t
Product	Food boxes	km	100	Lorry	Freezing	3.5–7.5 t

Currently, the company has 9 installed vending machines located at train stations, universities, and hospitals in London. Each vending machine can hold up to around 75 boxes of prepared food, and the stock is replenished when it goes below 25 packs (depending on the train station, it can take a few days). The retail kiosks are fitted with an integrated microwave, enabling the consumer to heat the food upon purchase. The product expiry date is 18 months from the production date when it is kept at a controlled temperature. However, the company is ensuring that no product spends more than 6 months in the freezer utilising the first in first out (FIFO) approach. The life cycle inventory of scenario A is shown in Table 3 and represents the total production of food boxes per year.

Table 3. Life cycle inventory per reporting flow.

Unit Process	Value	Unit
Inputs		
Vegetable preparation		
Beans	1200	kg
Pepper	4800	kg
Water	38.1	m^3
Plastic bag	8.4	kg
Electricity consumption blast-freezing	561.6	kWh
Electricity consumption short-term storage	232.8	kWh
Meat preparation		
Boneless chicken	6480	kg
Chicken wings	6480	kg
Sheep	3840	kg
Electricity consumption blast-freezing	561.6	kWh
Electricity consumption short-term storage	1555.2	kWh
Dry ingredient preparation		
Rice	18,000	kg
Food finalisation		
Paper box	1000	kg
Electricity consumption long-term storage	1509.1	kWh
Retail		
Electricity consumption vending machines	77,760	kWh
Outputs		
Products		
Food boxes	9900	kg
Solid Wastes		
Food losses	891	kg
Plastic bag	8.4	kg
Paper box	1000	kg
Liquid Wastes		
Wastewater	38.1	m^3

In scenario B, 10 sensors were installed to monitor the temperature and humidity to ensure that frozen food and raw materials for preparing the food are stored at the right temperature in the frozen food manufacturer's factory. The sensors considered in the REAMIT-LCA tool transmit data via a GSM-based communication network every 20 min.

3.3. Sensitivity Analyses

Two sensitivity analyses were performed to understand the influence of some parameters on the environmental impact assessment results. A sensitivity analysis was made to assess the effect of the food waste avoided on the environmental impacts. Therefore, a hypothetical scenario was considered in which the IoT technologies avoided wasting 2% of food products. In the tool, the environmental burdens avoided are modelled through the system expansion by substitution [69]. Credit is given to scenario B for avoiding additional food production to cover the losses in scenario A and all related upstream activities, such as transport and energy required to store and distribute the food.

The second analysis evaluated the influence of the number of vending machines on the environmental impacts. Currently, the company has 9 vending machines located at train stations, universities and hospitals in London. However, this number is expected to increase to 20 vending machines in the next 10 months. Therefore, this analysis evaluated the consequence of increasing electricity consumption due to the installation of new vending machines.

4. Results and Discussion

4.1. Environmental Impact Assessment and Hotspot Analysis

Figure 5 presents the relative contribution of each life cycle stage to the total impact obtained for the food company in the baseline scenario. Food raw materials production is the main hotspot of nine impact categories, global warming, terrestrial acidification, terrestrial ecotoxicity, land use, marine eutrophication, human toxicity, freshwater eutrophication, freshwater ecotoxicity and water consumption, contributing to 70–98.9% of the total impact in those categories.

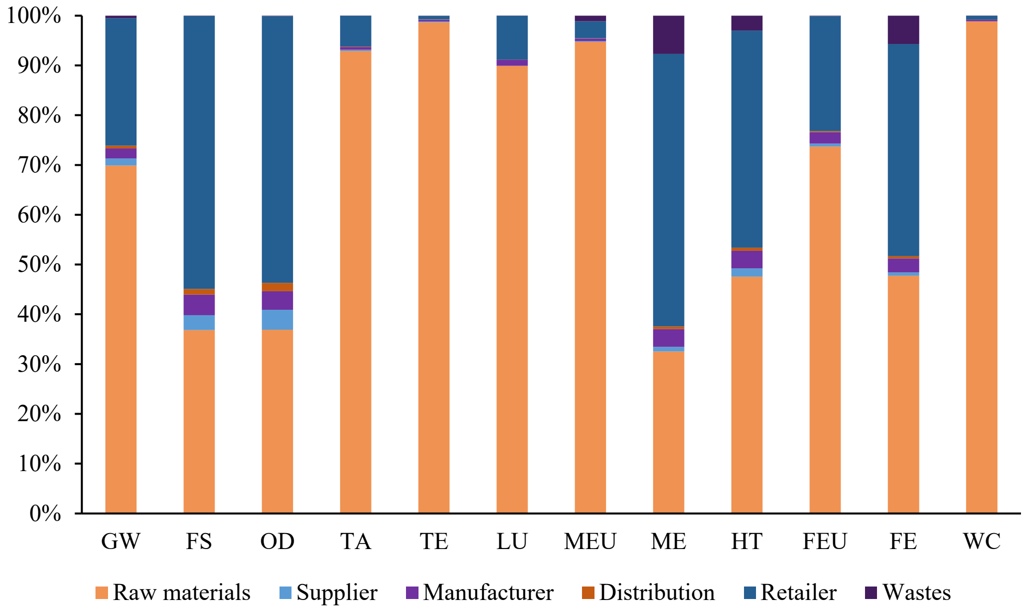

Figure 5. Relative contribution of each supply chain stage to the company's environmental impact.

Sustainable food production, therefore, must be prioritised to mitigate climate change, reduce water stress and pollution and restore lands to grasslands. The production of livestock (animals raised for meat, dairy and seafood products) contributes to emissions in several ways, for example, by producing methane through their digestive processes (enteric fermentation) [70–72]. Manure and pasture management, land use change, production of crops for animal feed, and fuel consumption also fall into this category [70,73]. Crops and vegetable production are mainly responsible for direct emissions, including elements such as the release of nitrous oxide from fertilisers and manure application, methane emissions from rice production, and carbon dioxide from agricultural machinery [74–76].

Water consumption and freshwater eutrophication are also valuable indicators of food production's environmental impact, as 70% of global freshwater withdrawals and 78% of global pollution of waterways are caused by agriculture [77]. The pollution of water bodies and ecosystems with excess nutrients is a major environmental problem [78,79]. Agriculture can represent the runoff of excess nutrients into the surrounding environment and waterways, which affect and pollute ecosystems with nutrient imbalances, especially from nitrogen and phosphate [80,81].

Contrary to many other areas of energy production where there are prospects for expanding the use of low-carbon energy, it is less obvious how agriculture may be decarbonised [82]. In agriculture, it is necessary to use inputs such as fertilisers to meet the rising demand for food, and it is impossible to stop animals from producing methane. Some solutions to decrease those impacts can include diet changes, food waste reduction, improvements in agricultural efficiency, and technologies that make low-carbon food alternatives scalable and affordable [83–85].

For the impact categories fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the retail stage was the main hotspot, representing 53.6–54.8% of the total impact. The retail stage consumed a high amount of electricity due to the vending machines used to store and sell the food boxes of the company. The electricity consumed during the retail stage was also relevant for human toxicity and freshwater ecotoxicity impact categories, contributing to around 42.6–43.6% of the total impact.

In this company, the effect of transportation (supplier and distribution stages) was not significant for any of the impact categories under analysis. Many could assume that eating locally is key to a low-carbon diet [86]. However, eating locally would only have a significant impact if transport was responsible for a large share of food's final environmental impact, but this is not the case for most foods. The greenhouse gas emissions from transportation make up a tiny amount of the emissions from food and what is consumed is far more important than where the food travelled from [87–91]. Overall, animal-based foods tend to have a higher footprint than plant-based; whether they are grown locally or shipped from the other side of the world matters very little for total emissions [92,93]. Therefore, eating less meat or switching to lower-impact meats such as chicken or eggs is the most effective way to reduce the environmental footprint [94–96].

Figure 6 presents the relative contribution of the REAMIT IoT technologies to the company's total impact disregarding the potential food avoided.

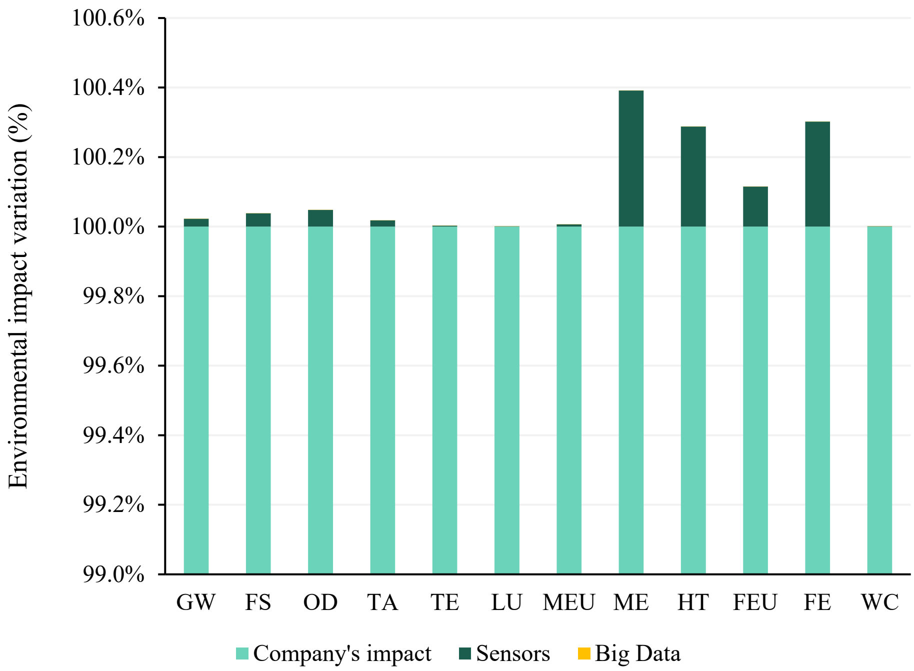

Figure 6. Relative contribution of the REAMIT IoT technologies implementation to the total impact of the food company (scenario B).

Although integrating IoT technologies to monitor temperature/humidity conditions can have many advantages, the environmental implications may also be analysed. In this study, it is possible to observe that this integration had little to no adverse effects on the company's overall impact. The contribution of the IoT technologies implemented in this study, including 10 sensors and a Big Data server to store and control the data, achieved a maximum impact contribution of 0.4% for the marine ecotoxicity category. Despite the impacts associated with implementing IoT technologies in this system, mainly due to components used to produce the sensors [97], there are still potential tangible benefits that should be considered. For example, a reduction in the environmental impact can be expected if part of the food waste is avoided due to implementing these technologies, which can equilibrate the additional impacts. The surplus food production to compensate for the waste may result in severe environmental and societal issues [98–100]. Therefore, to prevent food waste and the environmental impact related to this waste, it is advised to employ monitoring systems/technologies as the one suggested in this study. The potential avoided impacts resulting from the decreased amount of food waste due to implementing IoT technologies are shown in Section 3.2.

4.2. Sensitivity Analysis

Figure 7 presents the total impact obtained for the first sensitivity analysis, i.e., the influence of the monitoring IoT technologies on the environmental impacts considering a 2% reduction in food waste generation.

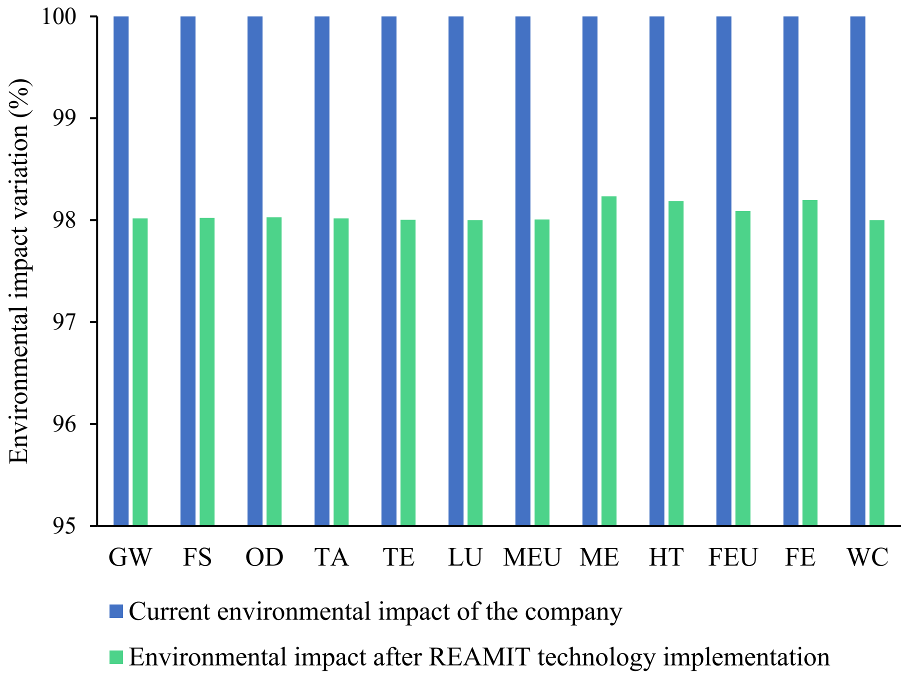

Figure 7. Results of the sensitivity analysis: effect of food waste reduction due to REAMIT technology implementation.

Food waste is linked to various adverse environmental effects [99,100]. When food is discarded, all the resources necessary to prepare, transport, process, and store it are also wasted. In addition, the environmental impact increases when food is discarded in the later stages of the supply chain because we also need to consider the energy and natural resources consumed in each stage [62]. Considering a food waste reduction of 2%, it is possible to decrease the environmental impacts from 1.7 to 2.1% (Figure 6). In the global warming category, this reduction represents the prevention of 2304 kg of CO_2eq per year. In addition to the environmental impacts avoided, reducing and preventing food waste can enhance food security, improve productivity and economic efficiency and promote resource and energy conservation [100,101]. In this scenario, additional food production would not be necessary to compensate for these losses. Therefore, contributing to the reduction of all downstream impacts observed during the food supply stages under analysis.

However, caution must be taken when affirming the positive effect of IoT technologies in reducing food systems' environmental impacts, as this can be a single case. Implementing IoT technologies in any system causes resource use, and if food waste reduction is not considered, the total impact of the organisation tends to increase. Furthermore, even considering the reduction, the overall balance of impacts depends on the amount of food avoided. The second sensitivity analysis in Figure 8 shows the influence of increasing the number of vending machines in the retail stage.

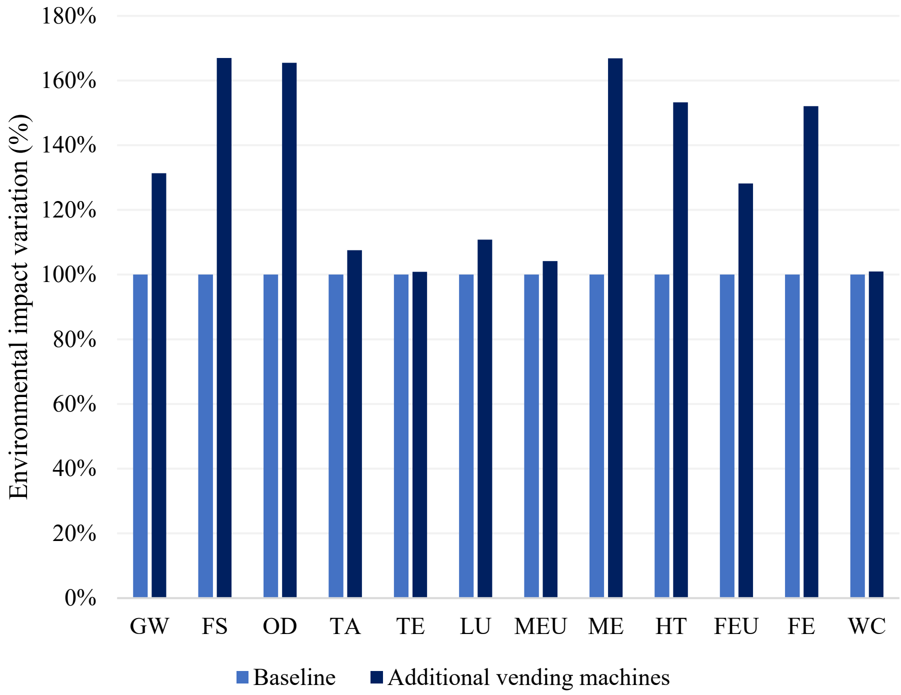

Figure 8. Results of the sensitivity analysis: effect of increasing the number of vending machines.

It was observed that the main categories negatively affected by this proposal were global warming, fossil resource scarcity, stratospheric ozone depletion, marine ecotoxicity, human toxicity and freshwater eutrophication and ecotoxicity. For fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the environmental impact increased by more than 60%, suggesting an environmental risk from using additional vending machines due to the high electricity consumption.

The environmental impacts related to electricity consumption are intrinsically linked to the electricity mix supplied in the country. In 2020, the electricity supplied in the UK came from 41% fossil-fuelled power (almost all from natural gas), 30.6% from renewable energy (including wind, solar and hydroelectricity), 16.1% from nuclear power and a small percentage from imports [102]. To the extent that more renewable energy sources like wind and solar are used to generate electricity, the total environmental impacts associated with using electricity could be reduced. However, it might take several decades for that to happen [103].

5. Conclusions

This paper describes an initial theoretical contribution to quantifying environmental effects related to food supply chains by integrating relevant insights from life cycle assessment science and sustainability theories. The result of this integration is a proposal for a prescriptive tool which explains how food waste can be addressed from an environmental point of view and applied to real-world problems. The excel-based tool is recommended for food producers, food supply chain companies (processing and logistics), local authorities, academics and digital technology providers. In addition, it has been populated with national average data (or closest equivalent) of six countries, i.e., Ireland, Germany, France, Luxembourg, the UK, and the Netherlands, due to the amount of interconnected food supply chains and huge food waste in these countries.

The tool is fully functional for different stages of the food life cycle, raw materials, suppliers, manufacturing, distribution, retail, and waste treatment. The REAMIT technology stage is treated as a sensitivity analysis where sensors and a Big Data server are used to reduce food waste. Credit was given to the system for avoiding additional food production to cover the losses and all related upstream activities avoided. The food consumption stage was not included, but the tool has been developed such that this stage can be added to the development of future modules. Using the developed LCA tool would assist food companies in understanding the benefits and drawbacks of moving toward sustainable food practices. Furthermore, using the tool can provide further insight into stages of the food supply chain that produce emissions that could be managed or minimised.

The tool was validated through a case study of a food manufacturing company in the UK that implemented IoT technologies to monitor environmental conditions, such as temperature and humidity, during the manufacturing stage. The tool proved to be suitable for determining environmental impacts and savings of the company under analysis and for understanding the environmental performance of their stages through a comprehensive framework. The LCA results provided by the tool showed that food raw materials production is the main hotspot of nine impact categories. For the impact categories fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity, the retail stage was the main hotspot.

The contribution of the IoT technologies to the company's total impact, including installing ten sensors and using a Big Data server, increased the company's impact by around 0.4%. However, it is expected that employing these monitoring technologies would prevent food waste generation and the associated environmental impacts observed during the food supply stages under analysis. Considering a food waste reduction of 2%, it is possible to decrease the environmental impacts by up to 2304 kg of CO2eq per year in the global warming category. However, the precise amount of food waste avoided due to IoT technologies implementation in this company is still under assessment, and further analysis is required. The sensitivity analysis regarding the performance of new vending machines showed that the impacts in the fossil resource scarcity, stratospheric ozone depletion and marine ecotoxicity categories increased more than 60%, suggesting an environmental risk due to the high electricity consumption.

Therefore, the results of this paper provide evidence of the benefits of using this tool to explore the problem of food waste and the solutions to achieve more sustainable food systems. The tool allowed the quantification of environmental effects such as climate change, resource use and other categories of impact. Through this holistic view, the user can identify which life cycle stage of the food company is the most resource, energy and impact intensive. This can help the user to identify the hotspots that need improvement in their operations or supply chains. Evaluating the supply chains can also help the user to determine which materials have the highest environmental impact. For foods with a blend combination of several ingredients, the REAMIT-LCA tool allows the comparison and testing out alternatives to make tactical sustainability decisions.

Further development of the tool in terms of functionality and adding food products and production processes is necessary. To make the REAMIT-LCA tool suitable for a larger group of companies, it is essential to extend beyond the current food product database to meet future users' specific needs. Additionally, the tool should be expanded with an option to select pre-defined inputs, from which the user can work. This will allow people in the food industry with little knowledge of LCA to use the REAMIT-LCA tool.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su15010718/s1, Video S1: REAMIT-LCA TOOL USER MANUAL.

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Abbreviations

AC, acidification potential; AD, abiotic depletion; AE, aquatic ecotoxic; CED, cumulative energy demand; CF, carbon footprint; CO_2, carbon dioxide; DEQ, damage to ecosystem quality; EC, ecotoxicity potential; EI, energy intensity; EU, eutrophication potential; FD, fossil fuel depletion; FEc, freshwater ecotoxicity; FEu, freshwater eutrophication; FIFO, first in first out approach; FT, freshwater aquatic toxicity; FS, fossil resource scarcity; GW, Global warming; HH, human health, HT, human toxicity; ISO, International Standard Organization; IoT, Internet of Things; LCA, Life Cycle Assessment; LCIA, Life Cycle Impact Assessment; LF, land footprint; LU, land use; MEc, marine ecotoxicity; MEu, marine eutrophication; NEW, North West Europe; PCB, printed circuit board; PMI, process material intensity; PW, process water; RM, resources metrics; SF, smog formation; SOD, stratospheric ozone depletion; TA, terrestrial acidification; TEc, terrestrial ecotoxicity; VBA, Visual Basic Applications, WC, water consumption; WS, water scarcity.

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An Organisational-Life Cycle Assessment Approach for Internet of Things Technologies Implementation in a Human Milk Bank

Tamíris Pacheco da Costa [1,*], James Gillespie [2], Katarzyna Pelc [3], Natalie Shenker [4,5], Gillian Weaver [4,5], Ramakrishnan Ramanathan [6] and Fionnuala Murphy [1]

1 School of Biosystems & Food Engineering, University College Dublin, Agriculture Building, UCD Belfield, D04 V1W8 Dublin, Ireland
2 School of Computing, Engineering and Intelligent Systems, Magee Campus, Ulster University, Northland Road, Londonderry BT48 7JL, UK
3 Bedfordshire Business School, University of Bedfordshire, Putteridge Bury, R. 220, Hitchin Road, Luton LU2 8LE, UK
4 Department of Surgery and Cancer, Imperial College London, Du Cane Road, London W12 0HS, UK
5 Human Milk Foundation, Rothamsted Institute, Daniel Hall Building, Harpenden AL5 2JQ, UK
6 Essex Business School, University of Essex, Southend Campus, Elmer Approach, Southend-on-Sea, Essex CO4 3SQ, UK
* Correspondence: tamiris.dacosta@ucd.ie

Abstract: Human milk banks (HMB) are responsible for screening and recruiting milk donors with surplus milk to their own infant's needs, followed by transporting, heat-treating (pasteurising) and microbiologically confirming the donor human milk (DHM) is safe to issue to vulnerable infants. Maintaining the safety and quality of DHM are vital requirements in HMB operations. DHM must be maintained in ideal temperature conditions throughout the whole period—from expression until delivery. In this regard, monitoring technologies (e.g., sensors, Big Data and the Internet of Things) have become a viable solution to avoid food loss, allowing prompt corrective action. Therefore, this study aimed to understand the trade-offs between optimising DHM transportation and the environmental impact of implementing such technologies. The environmental performance was carried out through an Organisational Life Cycle Assessment (O-LCA). The electricity consumed during milk storage is the main driver for the environmental impacts in this organisation, responsible for up to 82% of the impacts in ionising radiation. The transportation stage and the treatment of discarded DHM were also relevant for ozone formation and marine eutrophication, respectively. Considering the strategy to integrate monitoring technologies to control the temperature conditions during transportation and the reduction of milk discarded by 3%, an environmental impact reduction can be also observed. In some categories, such as global warming, it could avoid around 863 kg of CO_2-eq per year. The sensitivity analysis showed that the impacts of the HMB depend highly on the transport distance. In addition, changing the transportation mode from motorcycles to drones or electric vehicles can affect the environmental performance of this organisation. Therefore, human milk transport logistics must be studied in a multidisciplinary way to encompass all possible impacts of these strategies.

Keywords: environmental analysis; human milk bank; IoT technologies; milk waste; organisational LCA

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1. Introduction

Human milk is a valuable resource that has been proven to protect infants from a wide range of infectious and non-infectious diseases [1–3]. However, for numerous reasons, there are circumstances in which mothers cannot lactate at all or provide sufficient breast milk to meet their infant's needs in the immediate postnatal period [4]. In these situations, donor human milk (DHM) is considered the best substitute, especially for vulnerable and sick infants [4–6].

Human milk banks (HMBs) play a vital role by recruiting donors, processing, storing, and supplying milk in a safe and controlled manner [7]. Maintaining the quality of DHM is essential [8]. The milk must be maintained in ideal temperature conditions throughout the whole period—from the point of expression until its delivery [8,9]. In this regard, modern digital technologies (e.g., sensors, Big Data and the Internet of Things) have become viable solutions for continuous quality monitoring [10,11]. Continuous monitoring and timely corrective action can preserve milk quality and prevent unnecessary milk wastage [12].

While these digital technologies can help preserve the cold chain for DHM, the production of these electronic technologies can contribute to adverse environmental impacts [13,14]. The long-term environmental impacts of IoT technologies are unknown, but a noticeable amount of energy is needed to support the production and operation of digital devices [15]. Therefore, it is important to look at the trade-off between the value of milk waste avoided and the additional environmental impacts created due to the production of digital technologies. Understanding this trade-off is the primary purpose of this paper.

Life-Cycle Assessment (LCA) is a common methodology to understand such questions and is frequently used as a decision-support tool by food corporations [16,17] and policy-makers [18,19]. In addition, LCA enables the identification and quantification of critical hotspots and helps food companies to improve and minimise their environmental impacts through the optimisation of product management chains [20,21]. However, conducting a single-standing product LCA will only analyse a small part of the overall company. To address this issue, the Organisational Life Cycle Assessment (O-LCA) methodology set out in ISO/TS 14072 [22] is designed to assess the entire collection of goods and services of an organisation.

Therefore, this paper makes at least two contributions to the literature by carrying out the LCA. First, it uses a special case of LCA, namely O-LCA, for the analysis. Second, this is the first time the use of digital technologies to reduce DHM wastage is being evaluated using LCA. The paper is organised as follows. The theoretical background of LCA and O-LCA are discussed in the next section. The methodology of O-LCA is explained in detail in Section 3. Results are presented and discussed in Section 4. Additional sensitivity analyses are also performed in this section, including the case of using another digital technology, namely drones. Conclusions are presented in the last section.

2. Literature Review on O-LCA

Life cycle thinking has been applied to industry and politics during the past few years to comprehensively estimate product or services potential environmental impacts from cradle-to-grave [23,24]. It can help companies make their activities more environmentally friendly and less damaging to the environment [25]. In the recent decade, the knowledge of LCA methodology has progressed and evolved significantly [26]. Simultaneously, analysing potential environmental impacts on an organisational level is becoming increasingly attractive for a growing number of companies [27,28].

Although LCA was first created for product and service levels, there are still some limitations when expanding the unit of analysis at a whole organisational level. The main cause of this limitation is a lack of appropriate environmental data covering the entire portfolio of operations across the entire organisation [29]. As a result, academics have started investigating how to combine LCA with other methodologies to create a robust foundation for organisational decision-making [30–32].

To this extent, the UNEP/SETAC Life Cycle Initiative promoted the development of the organisational life cycle assessment. Through the "LCA for organisations" project, a guide paper was released in 2013 [33]. This provides instructions for conducting an O-LCA study containing references to current ISO standards and directives such as 14072 [22], 14040/44 [34,35], and 14001 [36]. It defines O-LCA as the "compilation and evaluation of the inputs, outputs, and potential environmental impacts of the activities associated with the organisation as a whole or portion thereof adopting a life cycle perspective" and aims to analyse the value chain of an organisation from the acquisition of the raw materials to its end-of-life through a multi-impact method, i.e., by taking into account a variety of environmental categories in order to prevent burden shifting [22]. The method is intended to be widely applied in different organisations, including, but not limited to, a sole trader, company, corporation, firm, enterprise, authority, partnership, charity or institution, or part or combination thereof, whether incorporated or not, public or private [22].

Most requirements and recommendations listed in ISO 14040/44 series standards for product LCA are equally appropriate for O-LCA. More specifically, the four-phase methodology used for product LCA is also used for the O-LCA implementation [22,35]. The fundamental distinctions between the two approaches refer to the scope and inventory phase, as the object under study. Furthermore, O-LCA should not be applied to compare different organisations or for corporate ranking, but rather to address improvements within the specific organisation [22].

Multiple organisational needs can be satisfied by this methodology: (i) identification of environmental hotspots along the whole company; (ii) environmental performance monitoring and management; (iii) support for strategic decision-making; and (iv) provide data for corporate sustainability reporting [33]. In general, O-LCA enables organisations to establish their sustainability strategies, enhances their operational activities, as well as supports the transition to more sustainable consumption and production models, towards a more resource-efficient and circular economy.

However, although interest in the LCA is growing quickly and significant explorative experiences are evolving, comprehensive and rigorous applications of O-LCA are not yet common practice, and further research is still required to comprehend how organisations should apply O-LCA. The most difficult aspects of an O-LCA study were found to be the classification of activities into direct, indirect upstream and downstream activities, producing the final report, evaluating the data quality and interpreting the results [29]. Therefore, offering solutions to these methodological issues will make method implementation easier, enabling environmental evaluations and impact reduction in different sectors. Moreover, no case applications have been published for non-profit associations, especially for HMBs.

3. Materials and Methods

3.1. General Rules for the Environmental Impact Assessment of Organisations

O-LCA follows the four-phase approach proposed by ISO 14040/44 for product LCA, including goal and scope definition, inventory, impact assessment and interpretation [34,35]. During the first phase of the analysis, the study motivation and the intended application are defined [22]. Particular attention must be paid to the scope phase since some features of the O-LCA differ from a conventional LCA procedure. The discrepancies are detailed below in accordance with the Guidance on Organisational Life Cycle Assessment [33]:

(i) It is necessary to disaggregate the reporting, i.e., the functional unit, into two components which correspond to description (reporting organisation) and quantification (reporting flow). All of the organisation's units and components shall be organised using either the control (financial or operational) or the equity share approach.

(ii) It is necessary to determine the reporting period (i.e., the specific period for which the organisation is being studied), as the results are only valid throughout that timeframe.

(iii) It is necessary to consider both direct and indirect emissions and resource utilisation in the system boundary. The first takes place within the reporting organisation, whereas the second occurs along the entire value chain associated with the organisation's operations.

(iv) It is necessary to include the resource consumption and emissions of the use and the end-of-life stages (i.e., waste disposal and treatment) of the products during the reporting period of a complete cradle-to-grave assessment. However, a cradle-to-gate perspective can be adopted if the organisation has no control over the use or end-of-life stages, eliminating the downstream phases.

The inventory phase describes the data collection procedures and the processing data relating to all inputs and outputs of the organisation considered [33]. It categorises them into activities following the organisation's value chain (direct activities, indirect upstream activities and indirect downstream activities) [22].

In the impact assessment, all inputs and outputs collected in the previous phase are converted into potential environmental impacts using specific characterisation factors [33]. The results of the impact categories taken into consideration are used to create a profile of the organisation's potential environmental impacts. Last, the interpretation phase requires a critical assessment of the result of an LCA study and allows us to derive conclusions and recommendations to support decision and communication strategies [22].

3.2. Description of the Case Study

The study focuses on one facility where the entire operations occur, the Hearts Milk Bank, located within the Rothamsted Institute in Hertfordshire. Hearts operates as part of the Human Milk Foundation (HMF), a charity dedicated to creating nationally equitable milk bank services. The mission of the charity is to support families facing feeding challenges in neonatal intensive care units through the provision of education and donor human milk (DHM), as well as where a bridge to a full milk supply is needed or lactation is not possible. Access to DHM is of particular importance for premature and very sick babies whose mothers temporarily or in the long term are not able to provide any or enough of their own milk. Hospital neonatal units are charged a fee to cover the milk bank's costs, but DHM and lactation support is provided free of charge to families who would not currently qualify on the National Health Service. The provision of the DHM is under the oversight of a healthcare professional.

HMBs play a vital role by recruiting donors, processing, storing and supplying donor milk to neonatal units and similar settings in a safe and controlled manner [7]. However, if the milk does not pass the rigorous microbiology tests both before and after pasteurisation, it is discarded [37]. The main factor involved in human milk wastage is microbiological contamination, which represents around 10–12% of donated milk being discarded currently [38,39].

Therefore, a strategy implemented in this particular HMB to ensure that the milk has remained in optimal conditions from the point of expression until fed to a vulnerable infant is to monitor the temperature and humidity during milk transportation using IoT technologies. For every journey, a sensor was installed to monitor the milk in the right condition of temperature and humidity. The sensors transmit the temperature/humidity information to a Big Data server, and alerts are sent when the temperature exceeds the acceptable limit. Detailed information on the monitoring system will be presented in the following sections.

3.3. Definition of Goal and Scope

The goal of the assessment is to assess the potential environmental impacts of a single research-focused UK HMB and the potential environmental savings due to implementing a monitoring system based on IoT technologies.

Table 1 summarises the main characteristics of the organisation analysed in this study. The reporting unit was defined as "human milk management during one year of HMB operation". The reporting flow is, therefore, 3936 L of human milk, which was the volume of human milk donated between January and December of 2021 (reference period).

The consolidation method applied was the total control over operational terms; i.e., the reporting organisation has full operational control on how the human milk is distributed to final consumers, used and disposed of. Under this approach, the organisation accounts for 100% of the impacts from units over which it has operational control. All activities and related life cycle processes of the reporting organisation were considered according to ISO/TS 14072. Four experience-based pathways are described in the UNEP/SETAC report [33] for conducting an O-LCA. The reporting organisation had initial environmental experience and information to perform a gate-to-gate analysis; therefore, it fits the "pathway 2".

Table 1. Organisational life cycle assessment characteristics.

Criteria	Specific Features
Reporting organisation	Human milk bank in the UK
Organisation size	Small size (<50 employees and volunteers)
Intention of application	Environmental performance assessment and improvement, identification of environmental hotspots, strategic management and control
Targeted audience	Disclosed to the public, including HMB associations, policymakers, funding sources and costumers
Reporting period	January–December 2021
Reporting unit	Human milk management during one year of operation
Reporting flow	3936 L of human milk
Consolidation method	Operational control
Experience-based pathway	Existing environmental assessment gate-to-gate (Pathway 2)
System boundary	Cradle-to-grave (excludes the recruitment, selection, approval, consent and education of milk donors and the milk defrosting and consumption by the recipients).
Data collection method	Top-down: direct activities data were collected through company interviews. Indirect upstream and downstream activities data were taken from Ecoinvent database.

Two scenarios were built to determine the effect of IoT technologies on monitoring/controlling the temperature and humidity during milk transportation on the environmental impacts of the HMB. Scenario A represents the baseline scenario and includes the processes associated with the HMB. Scenario B follows the same processes as scenario A but includes the IoT technologies used to monitor the transport conditions.

The system boundaries are illustrated in Figure 1 and follow a cradle-to-grave approach. The consolidation method applied allows the inclusion in the system boundaries the processes over which the organisation has the full authority to introduce and implement its operating policies at the operation. In this study, the processes include milk collection, storage, first transportation from the donor's home/hospital to the HMB, processing (screening, pasteurisation, packaging and storage), second transportation from the HMB to the hospital/recipient home and final treatment provided to all solid waste generated (landfill and recycling).

Scenario B also comprises digital sensors for measuring the specific parameters, the Big Data server and the human milk avoided. Both scenarios exclude the recruitment, selection, approval, consent and education of milk donors, the milk defrosting and consumption by the recipients, as well as the energy consumed by breast pumps and the freezers at donors' home/hospital. The use of containers to collect the milk was included in the boundaries, as they are provided by the HMB and are part of the bank's operational control.

3.4. Life Cycle Inventory

Data collection followed the recommendations for O-LCA provided by UNEP/SETAC [33]. According to its guidance, the system should include all inputs and outputs from direct and indirect activities. Direct activities represent the processes owned or controlled by the reporting organisation, while indirect activities are related to the consequences of the reporting organisation's actions that occur at sites controlled by other organisations of the value chain. Figure 2 shows the inputs, outputs and direct and indirect activities under analysis.

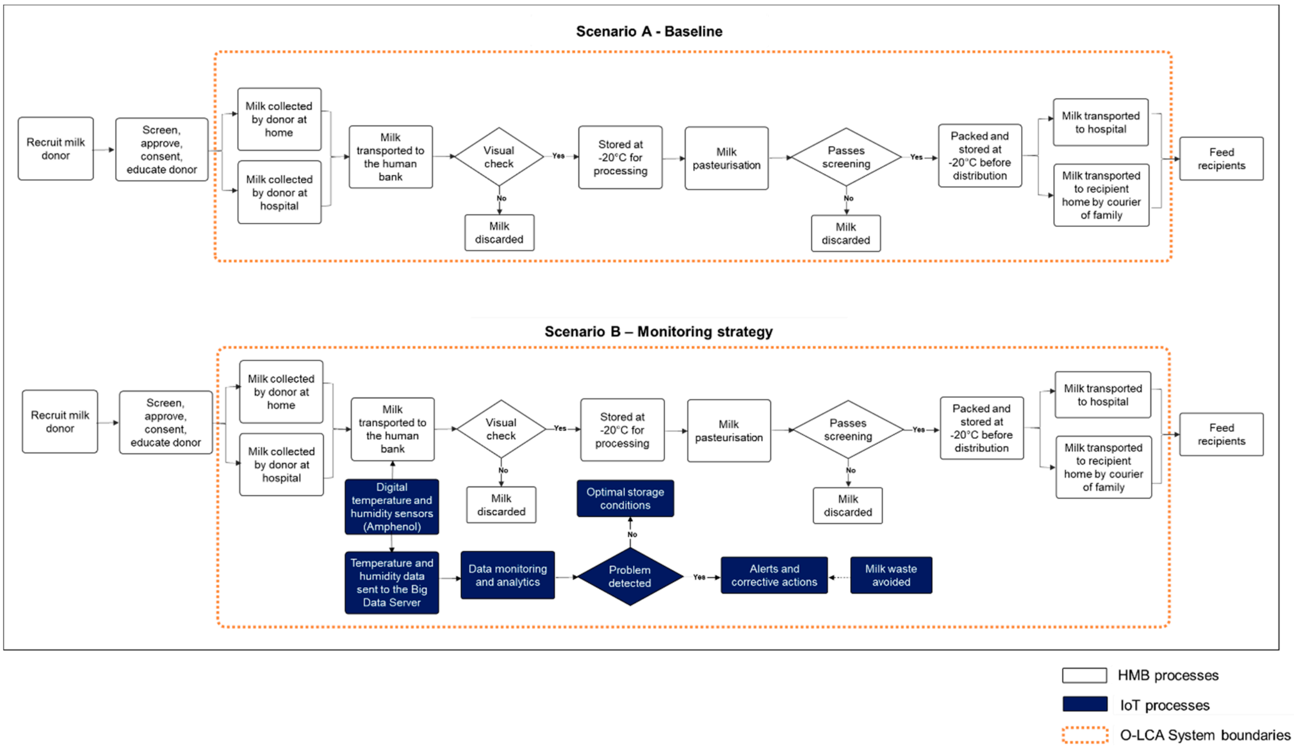

Figure 1. Schematic representation of the system boundaries. (**A**) refers to the baseline scenario, and (**B**) refers to the monitoring strategy implemented in the organisation.

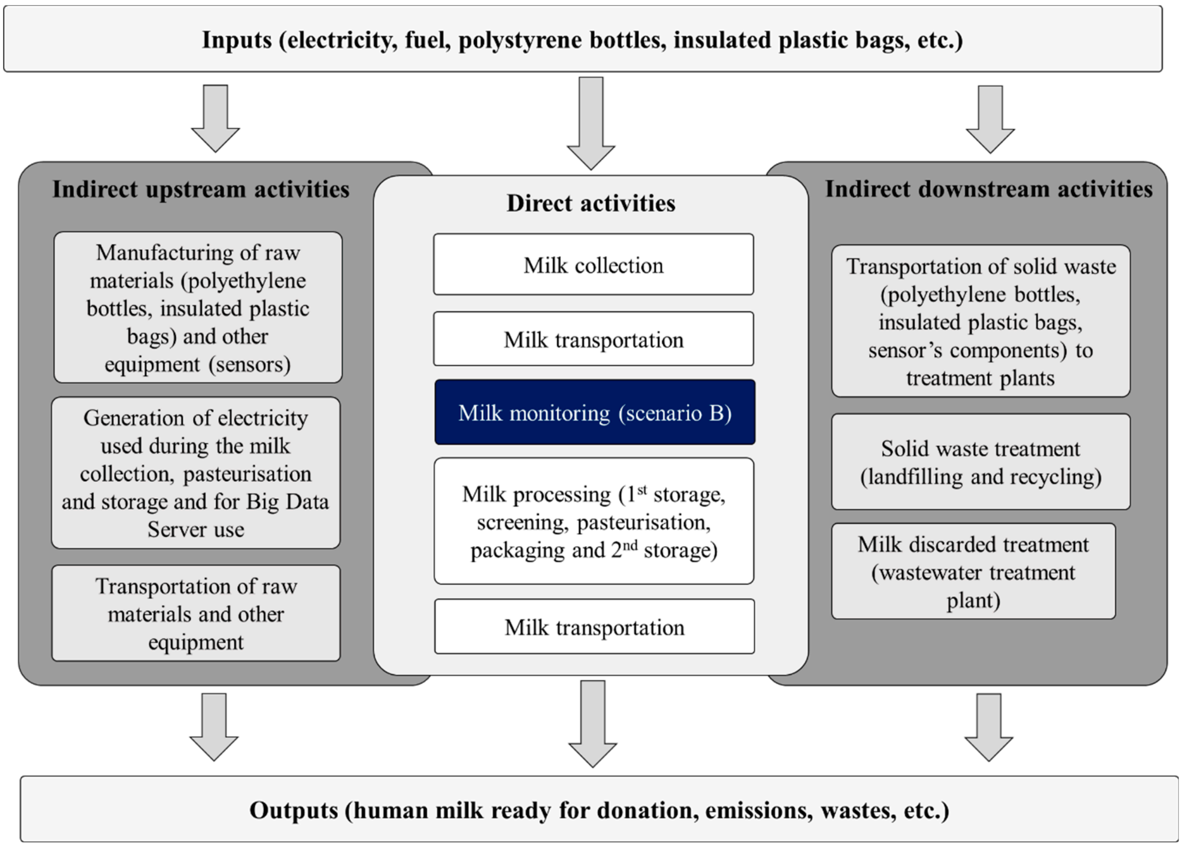

Figure 2. Inputs, outputs, and activities (direct and indirect) of the reporting organisation.

In this study, the data collection method was defined as a top-down approach, that is, an inventory-oriented approach. It considers the reporting organisation as a whole and adds upstream models for all inputs of the organisation and downstream models for all outputs [33]. Therefore, specific data should be used for direct activities. There are two main methods to quantify the inventory for direct activities: direct measurement or calculation. In this study, direct quantification of all resources was systematically made by the reporting organisation, including a detailed list of all materials used and the energy consumed. Calculation procedures were used to quantify the indirect activities and required the use of activity data and consumption/emission factors.

Direct activities include energy use, milk collection, processing (storage, screening, pasteurisation and packaging) and transportation. Indirect upstream activities include extraction and manufacturing of raw materials (e.g., polyethylene bottles and insulated plastic bags), generation of electricity and transportation of the raw material to the HMB. Indirect downstream activities are related to the transportation of solid waste to the final destination, solid waste treatment (landfilling and recycling) and treatment of discarded DHM. The life cycle inventory of direct activities (scenario A) can be found in Table 2.

Table 2. Life cycle inventory of an HMB in the UK per reporting flow.

Unit Process	Value	Unit
Inputs		
Milk collection		
Polyethylene bottles	388	kg
1st transportation		
Diesel	1006	L
Insulated plastic bags	2.83	kg
Dry ice	5.62	kg
Milk processing		
Electricity consumption—1st storage	4795	kWh
Electricity consumption—pasteurisation	414	kWh
Electricity consumption—2nd storage	33,350	kWh
Polyethylene bottles	388	kg
2nd transportation		
Diesel	670	L
Insulated plastic bags	2.83	kg
Dry ice	5.62	kg
Outputs		
Products		
Human milk ready for donation	3361	L
Liquid wastes		
Human milk discarded	575	L
Solid wastes		
Polyethylene bottles	776	kg
Insulated plastic bags	5.67	kg
Air emissions (transportation)		
CO_2, fossil	3937	kg
CO, fossil	482	kg
CH_4, fossil	10.5	kg
NMVOCs	117	kg
N_2O	0.05	kg
NO_x	11.2	kg
SO_2	20.1	g
Particulates	1.59	kg

3.4.1. Milk Collection

Breast milk is expressed manually or using electric or manual breast pumps. The milk is collected and stored in high-density polyethylene (HDPE) containers (free of bisphenol-A, bisphenol-S, DEHP and phthalates). The containers are single-use and are recycled after their end-of-life. The minimum volume required for donation is 2 litres per collection due to logistical limitations, maximising efficiency of milk bank processes and operational costs of donor recruitment. The total time to collect the minimum volume of milk required ranges from 3 days to 3 months, depending on the mother's circumstances and her physiology.

Donors are responsible for freezing and controlling the temperature while the milk is under their responsibility. The HMB provides donors with a standard domestic freezer thermometer to check the freezer's temperature and requires them to record the temperature daily. The HMB under study typically recruits 40–50 donors per month and serves approximately 4000 infants annually.

3.4.2. Milk Transportation

Donated milk is normally transported by blood bike motorcycle volunteers. Normally, between one and six volunteers make the transportations per day, totalling about 20 volunteers working at the HMB. The milk is transported using insulated and weather-resistant bags of three different sizes, small (30 × 25 cm), medium (35 × 35 cm) and big (70 × 35 cm). The durability of the bags was assumed to be 10 years and was considered that they are recycled after their end-of-life. The average amount of human milk transported per bag is 7 litres. The insulated bags can keep the milk frozen for up to 4 h. If the transport time is longer, it is necessary to use dry ice. It was assumed that 1% of the trips require the use of 1 kg of ice, although this is likely an overestimate.

The average transport distance during the first transportation (from donor/hospital to HMB) is around 50 miles, but it can achieve up to 100 miles per route. For calculation purposes, it was considered the average distance (mean: 75 miles). The second transportation mode (from the HMB to the hospital neonatal units/recipient home in the community) is also made by motorcycle volunteers, but the average distance is 50 miles. The diesel-related emissions to air during combustion were taken from Ecoinvent [40].

3.4.3. Milk Processing

The recently arrived frozen milk is unloaded, labelled for identification and transferred to freezers that maintain internal temperatures of at least −20 °C. Four medical-grade freezers (262 L capacity) and seven upright food-grade freezers (365 L capacity) are used to store the incoming milk, while three fridges (400 L capacity) are used for defrosting the milk at the HMB. The milk can be kept frozen for some weeks before the first screening. The electricity consumed by each medical freezer is equal to 2.2 kWh per day, while the food freezers consume around 12 kWh per day and the fridges 4.4 kWh. The milk is then defrosted, and the contents of 10 to 20 containers are pooled by being poured into stainless steel jugs and gently stirred before decanting into 50, 100, or 200 mL sterile containers. Samples from each batch are taken for microbiological analysis. Milk is not pooled between different donors.

After this process, the milk is pasteurised. The method involves heating the human milk at around 62.5 °C for at least 30 min. The HMB has two pasteurisers, which process up to 19 L of milk and consume 2 kWh per cycle. A sample from each batch is screened after pasteurisation for microbial contamination, and milk is discarded if microbiological thresholds are exceeded in accordance with the NICE Clinical Guideline [41]. The processed milk is frozen and stored in freezers with a cooling capacity of −25 °C. The milk is stored in polyethylene containers with different capacities (50–200 mL) depending on the final use (infants in hospital or recipients at home). The milk can be stored for up to 6 months after the date of the first expression until expiration, but it is typically used in less than 3 months.

Approximately 330 L of human milk were managed per month in the calendar year, but output from Hearts is increasing by approximately 40% year on year. The percentage of milk discarded monthly (considered unsuitable for consumption) ranged from 5.1% to 17.9% over the last year (mean: 11.7%; September 2021–August 2022), with the highest failure rates during the summer months (June–August).

3.4.4. Milk Monitoring (Scenario B—IoT Technologies Implementation)

A total of 12 sensors were installed to monitor the milk and ensure it remained in the right temperature and humidity condition. The Eagle datalogger (Digital Matter) was selected as the IoT platform, which formed the basis of the temperature and humidity monitoring system deployed in this human milk bank. The logger is an IP67-rated rugged cellular IoT device, supporting a range of inputs for various IoT applications. Each logger has four cell long-life power alkaline batteries, each with a capacity of 7800 mAh. Therefore, no other electricity or energy is required during the use phase.

Onboard, the logger contains a printed circuit board (PCB) with an array of sensor inputs, a GPS module and an accelerometer for geofencing and movement detection and is equipped with a cellular modem and sim card allowing the device to run on the IoT low-power LTE-M (CAT-M1) 4G network for data transmission. For sensing, the eagle was equipped with a T9602 temperature/relative humidity (T/RH; ±2% RH, ±0.5 °C, 0.01 °C resolution) sensor probe (Amphenol, Wallingford, CT, USA).

The sensors used in this study were manufactured in South Africa, but most of the electronic components of the PCB were produced in China as well. The sensors were transported to the UK in a container ship as a whole component, and the batteries were also included. A freight lorry was used for transportation within the UK. Transport distances were calculated based on the distance from the production site to the HMB. The air emissions due to the combustion of diesel and heavy fuel oil during the sensor transportation were taken from Ecoinvent [40]. The electricity consumed during the manufacturing phase for mounting the PCBs and the sensors was taken from Chiew and Brunklaus [42].

The sensors were installed inside the bag of each volunteer blood biker making regular journeys. Installation of the sensor is performed manually, and no environmental burden was assumed. The life span of the sensor is around 10 years, depending on the environmental conditions [42]. According to the supplier, the batteries last about 4 years, considering one measurement every 20 min. However, in this study, the sensors measure the conditions every 2 min; therefore, it is estimated that the batteries will last about 5 months each.

For the end-of-life phase of the sensor's components, it was considered that the sensor housing, the copper cables, and the screws were recycled, while the PCB was reused, and the batteries and the antenna were sent to a landfill, as they cannot be recycled at this time. It was considered that 100% of the solid wastes reach the final disposal (regardless of the technique used). The sensors components were weighted, and the complete inventory data of raw materials, manufacturing, use and end-of-life were described in Table 3.

The sensors measure the conditions and send the collected information to a Big Data server. The server sends alerts when the temperature exceeds the acceptable limit (above −15 °C). The alert is sent via email or SMS to designated individuals at the HMB. The Big Data Server comprises one unit of computer equipment, a redundant power supply (1600 W), processors and storage drives. The estimated electricity consumption of the server is 1152 kWh per month. Each row of data generated per recording occupies around 87 bytes in the server. The sensors are configured to record data every 5 min while in a trip or every 12 h outside of a trip. The electricity consumption was allocated according to the use of the server space; i.e., 8.1% of the space in use was due to the sensors installed at the HMB. For the internet connection, the Ecoinvent database was used in the model. Whenever possible, regionalised datasets were used to model the foreground processes.

Table 3. Life cycle inventory of sensor manufacturing, transportation and use per single unit working one year.

Unit Process	Value	Unit
Inputs		
Raw materials		
Printed circuit board	1.576	g
Copper flexible cable	1.114	g
Antenna with ceramic tip metal probe	0.530	g
Alkaline batteries	219.2	g
Stainless steel screws	0.384	g
Housing top and bottom	6.746	g
Manufacturing		
Electricity	0.0044	kWh
Transportation		
Heavy fuel oil (container ship)	0.00062	L
Diesel (freight, lorry)	0.00024	L
Outputs		
Products		
Sensor	1	unit
Solid wastes		
Printed circuit board	1.576	g
Copper flexible cable	1.114	g
Antenna with ceramic tip metal probe	0.530	g
Alkaline batteries	219.2	g
Stainless steel screws	0.384	g
Housing top and bottom	6.746	g
Air emissions (transportation)		
CO_2, fossil	2.617	g
CO, fossil	0.002	g
CH_4, fossil	0.034	mg
NMVOCs	0.002	g
N_2O	0.134	mg
NO_x	0.047	g
SO_2	0.028	g
Particulates	0.004	g

3.5. Life Cycle Impact Assessment

The life cycle impact assessment was mainly modelled using the software OpenLCA v1.10.3. The characterisation factors used in this study for the impact assessment are those of the ReCiPe 2016 method at the midpoint level following a hierarchical perspective [43]. The following environmental impact categories were included: global warming (GW), ozone formation–human health (OH), ozone formation–terrestrial ecosystems (OT), stratospheric ozone depletion (SOD), ionising radiation (IR), fine particulate matter formation (PM), freshwater eutrophication (FEu), marine eutrophication (MEu), freshwater ecotoxicity (FEc), marine ecotoxicity (MEc), terrestrial ecotoxicity (TEc), human carcinogenic toxicity (HTc), human non-carcinogenic toxicity (HTnc), terrestrial acidification (TA), fossil resource scarcity (FS) and water consumption (WC).

3.6. Sensitivity Analyses

Four sensitivity analyses were performed to understand the influence of some parameters on the environmental impact assessment results. A sensitivity analysis was made to assess the influence of the monitoring IoT technologies at the transportation stage on the milk waste avoided and, consequently, on the environmental impacts. At this moment it is not possible to estimate the exact amount of human milk wasted during the transportation stage, and the value used in this sensitivity analysis considers two hypothetical scenarios, where: (1) the IoT technologies avoided discarding 1% of human milk, and (2) 3% of human milk discarded due to transportation issues was prevented. The environmental burdens avoided were modelled through the system expansion by substitution [44]. Credit was given to scenario B for avoiding additional human milk production to cover the losses in scenario A and all related upstream activities, such as collection, transport and energy required to store and pasteurise the milk.

The second analysis evaluated the influence of transportation distances on the results. The assumed distances of the first transportation (from the donor's home/hospital to the HMB) used in the baseline scenario are related to the average distance. The distances were changed to make the assessment more representative of other regions. Therefore, the transport distances were adjusted to the extreme values of the baseline distances (i.e., 50 and 100 miles).

Another sensitivity analysis assesses the influence of substituting motorcycle volunteers with delivery drones. Drones have found applications in many civil sector areas during the last decade. A drone is an aircraft without a human pilot on board whose flight is controlled either autonomously or under the remote control of a pilot on the ground or in another vehicle. Selecting this analysis was based on the Human Milk Foundation ambition to reduce reliance on fossil fuels for transportation purposes [45]. Ongoing projects aim to use drones to make 10% of the first and second transportation. In this scenario, the energy model used to determine the drone's electricity consumption is based on the specifications of the Wingcopter 198 drone with 8 lift rotors [46]. The delivery includes flying at 18 km/h and descending to the delivery site with a payload of 5 L. The return trip is similar but without the payload. The drone has two Li-ion batteries of 814 Wh each, which allows a range of 75 km considering ideal conditions (no wind, sea level altitude, 15 °C air temperature) and ideal operation (ideal cruise speed, 20% battery reserve, standard payload form factor).

The last sensitivity analysis evaluates the substitution of 10% motorcycles for electric vehicles. In this scenario, the impact of the carried payload of human milk was also examined. Two scenarios were considered: (1) the electric vehicle transports 10 L per journey, and (2) 50 L of milk is transported per journey. The average energy consumption, 200 Wh/Km, was taken from EV [47] and is based on real-world values corrected for multiple versions of vehicles.

4. Results and Discussion

4.1. Environmental Impact Assessment and Hotspot Analysis

Figure 3 presents the relative contribution of each unit process to the total impact obtained for the baseline scenario (A). Human milk transportation is the main hotspot of six impact categories: global warming, ozone formation (human health and terrestrial ecosystems), terrestrial ecotoxicity, human non-carcinogenic toxicity and fossil resource scarcity. The contribution of first and second transportation combined represents 39.3–71.6% of the total impact in those categories. For global warming, carbon dioxide (CO_2) emitted from diesel combustion is the main contributor in this category. Other relevant emissions to consider during diesel combustion include non-methane volatile organic compounds (NMVOC) for ozone formation, zinc (Zn) and human non-carcinogenic toxicity and copper (Cu) for terrestrial ecotoxicity.

For ionising radiation, the electricity consumed during the second storage of human milk is the main hotspot (82% of the total impact), followed by the first storage (12%). The electricity consumed during milk storage is also relevant for stratospheric ozone depletion, fine particulate matter formation, freshwater eutrophication, freshwater ecotoxicity, marine ecotoxicity, human carcinogenic toxicity, terrestrial acidification and water consumption. Regarding marine eutrophication, the treatment of discarded milk represents 80.7% of the total impacts and was essentially due to the emissions of nitrate and ammonium to water.

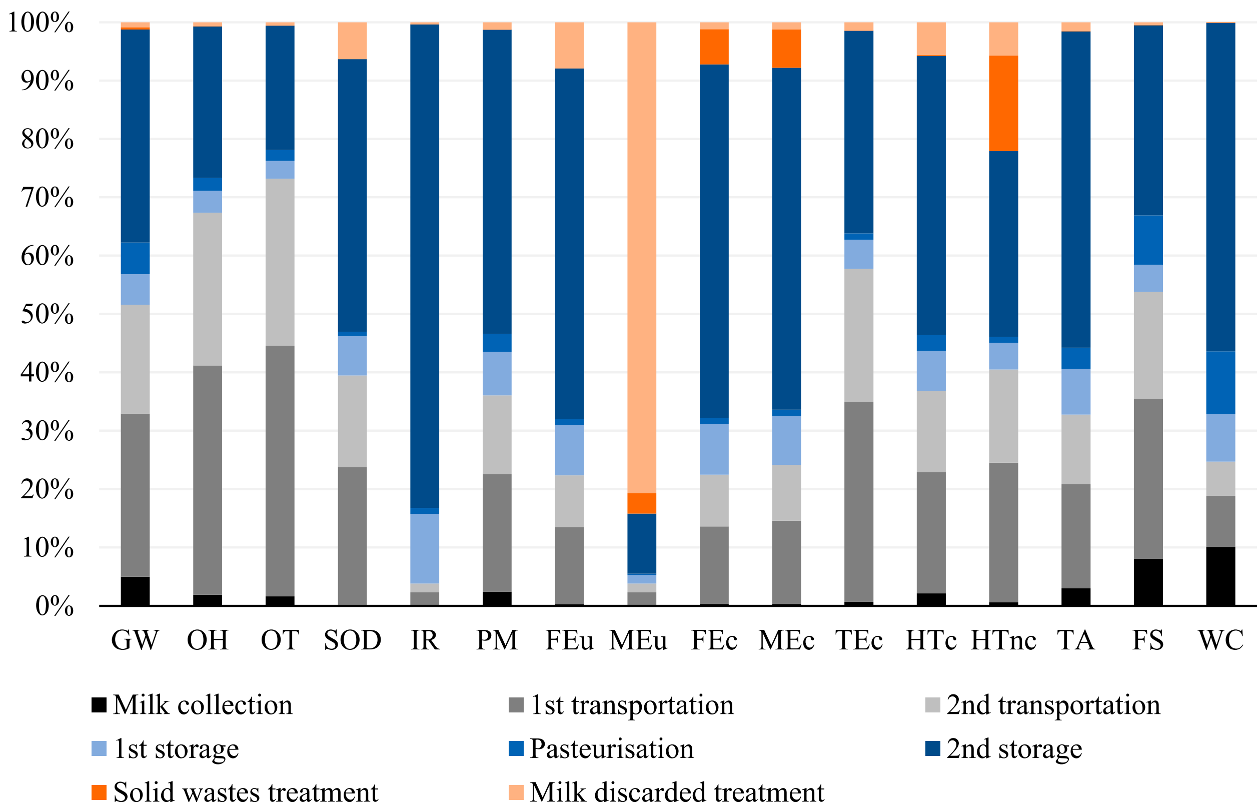

Figure 3. Relative contribution of each source to the total impact of the baseline scenario (A).

Figure 4 presents the relative contribution of manufacturing, transportation and use for the total impact of the sensors used in this study. It was observed that batteries (manufacturing and use) are the main hotspot for the sensor life cycle, followed by the printed circuit board for all impact categories. The batteries represent 62–96% of the total impact, while PCB can achieve 3.5–36.6%. In this system, nitrogen oxide (NOx) is the main responsible for the impacts on ozone formation (human health and terrestrial ecosystems), while SO_2 is relevant for the impacts on fine particulate matter formation and terrestrial acidification. Copper (Cu) present during the batteries manufacturing is responsible for a great part of the impacts on ecotoxicity categories, including freshwater, marine and terrestrial, and Chromium VI is the most important contributor to the impact in the human carcinogenic toxicity category.

Figure 5 presents the IoT technologies' relative contribution to the HMB's total impacts regarding the potential milk avoided. Although integrating IoT technologies to monitor temperature/humidity conditions can have many advantages, the environmental implications of using these technologies have been scarcely debated. On one hand, these technologies substitute physical processes and may help avoid impacts, which Weber et al. [48] described as "moving bits instead of atoms". On the other hand, they use electronics, an impact-intensive technology. In addition, the energy consumption of electronic products is far from insignificant. Consequently, the environmental impacts these technologies help to avoid must be balanced with the environmental impacts they generate themselves, keeping in mind that these impacts may not be of the same nature and therefore lead to dilemmas. In Figure 5, it is possible to observe that this integration did not adversely affect the organisation in a significant way. The contribution of the IoT technologies implemented in this study, including 12 sensors and a Big Data server to store and control the data, achieved a maximum impact contribution of 2.3% for the freshwater ecotoxicity category.

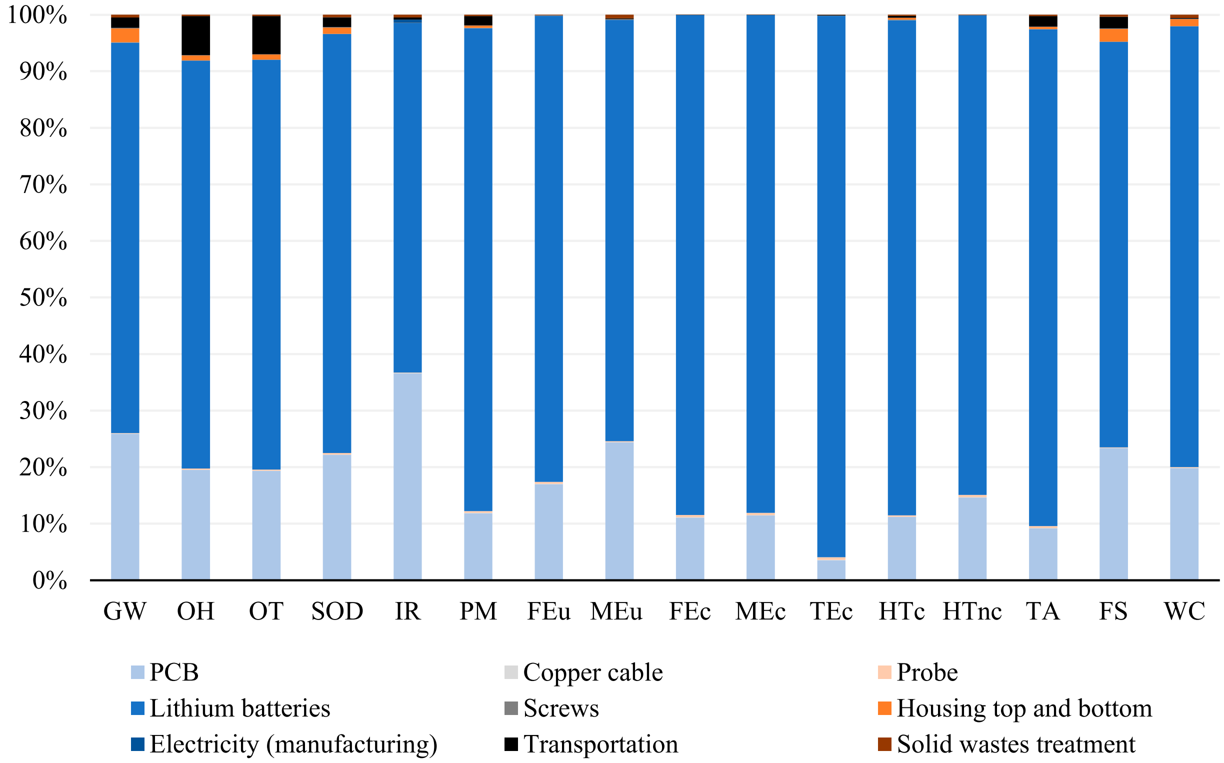

Figure 4. Relative contribution of each source to the total impact of sensors.

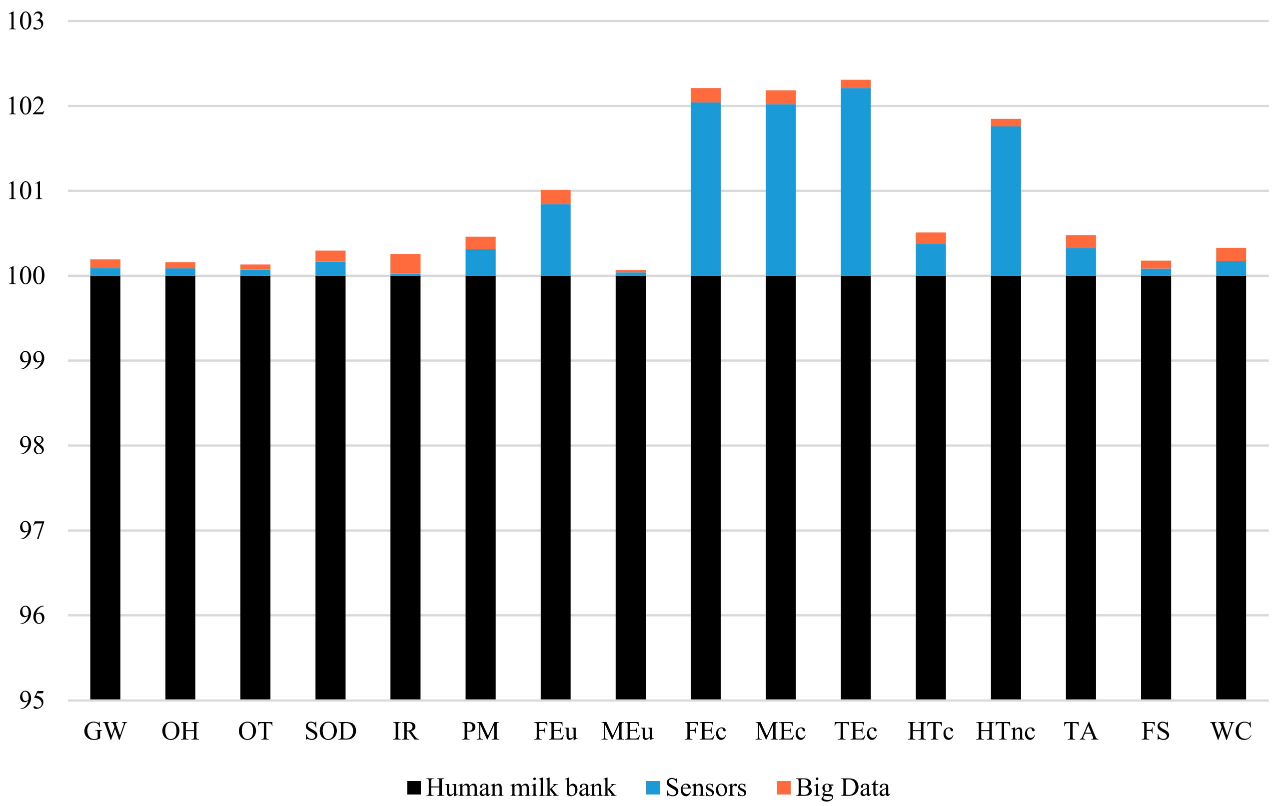

Figure 5. Relative contribution of each source to the total impact of the monitoring strategy scenario (B), disregarding the credits due to food waste avoided.

The main impact categories affected by the implementation of sensors are freshwater ecotoxicity, marine ecotoxicity, terrestrial ecotoxicity, human non-carcinogenic toxicity and freshwater eutrophication, especially due to the use of batteries as a source of energy. The common environmental side effects of metals mining to produce the batteries are increased salinity of rivers, contaminated soil and toxic waste, ground destabilisation and water and biodiversity loss [49]. The substitution of these batteries for more environmentally friendly alternatives can be a strategy to mitigate their associated impacts [50,51]. For about a decade, scientists and engineers have been developing sodium batteries, which replace the metals used in current batteries [52]. Another alternative can be supercapacitors and ultracapacitors. These devices offer advantages over batteries in lifetime, power density and resilience to temperature changes [53]. They also benefit from high immunity to shock and vibration. However, they can be high initial costs and provide low energy density [54].

The electricity consumed to store and control the data by the Big Data server contributed to a slight increase (<1%) in the impacts mainly for the following categories: ionising radiation, water consumption, fine particulate matter formation and freshwater eutrophication. However, a reduction in the environmental impact can be expected if human milk waste is avoided, which can equilibrate the additional impacts caused by the introduction of monitoring technologies. The surplus production of food to compensate in case of waste could cause a significant amount of environmental and social problems [55–57]. Therefore, it is recommended to use monitoring systems/technologies, such as the one proposed to avoid food waste and the environmental footprint associated with these wastes. The potential avoided impacts resulting from the decreased amount of milk waste discarded due to the implementation of IoT technologies are shown in Section 4.2.

4.2. Sensitivity Analysis

Table 4 presents the total impact obtained for the first sensitivity analysis, i.e., the influence of the monitoring IoT technologies on the environmental impacts considering 1–3% reduction in the total milk discarded. Figure 6 shows the percentage change based on the baseline scenario.

Table 4. Total results of the impact assessment associated with the baseline scenario (A) and the scenarios representing the implementation of monitoring technologies (B).

Impact Category	Unit	Scenario A	Scenario B (1% Waste Reduction)	Scenario B (3% Waste Reduction)
GW	kg CO_2 eq	30,749	30,501	29,886
OH	kg NOx eq	135	134	131
OT	kg NOx eq	166	165	161
SOD	kg CFC_{11} eq	0.0129	0.0128	0.0125
IR	kBq Co-60 eq	8489	8426	8256
PM	kg $PM_{2.5}$ eq	50.5	50.3	49.2
FEu	kg P eq	7.77	7.77	7.62
MEu	kg N eq	4.22	4.19	4.10
FEc	kg 1,4-DCB	2320	2348	2302
MEc	kg 1,4-DCB	2972	3007	2947
TEc	kg 1,4-DCB	103,960	105,318	103,239
HTc	kg 1,4-DCB	1112	1106	1084
HTnc	kg 1,4-DCB	27,857	28,094	27,536
TA	kg SO_2 eq	126	125	122
FS	kg oil eq	9037	8962	8781
WC	m^3	203	201	197

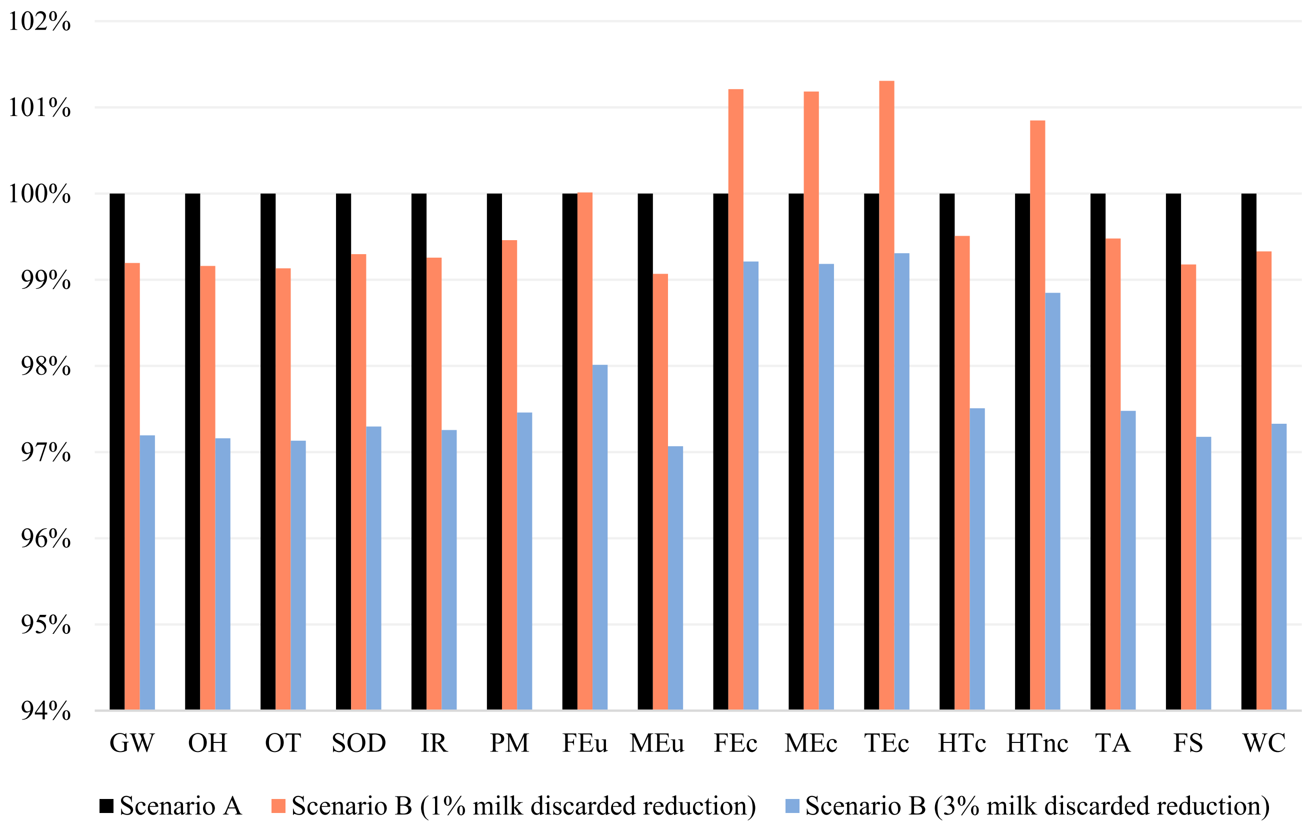

Figure 6. Results of the sensitivity analysis: effect of human milk discarded reduction.

A 1% reduction in discarded milk can decrease the environmental impacts from 0.5 to 0.9 % in some categories. Marine eutrophication and ozone formation were the impact categories more positively affected. However, this reduction is not sufficient to offset the impacts added to the system due to the implementation of IoT technologies in four categories: freshwater, marine and terrestrial ecotoxicity and human non-carcinogenic toxicity.

However, when milk discarded achieves a reduction of 3% in the second scenario, the impacts on the global warming category are reduced by 863 kg of CO_2-eq per year in this organisation. In this scenario, the control of the milk conditions proved to be relevant to the reduction of impacts related to air emissions and resource consumption. In this particular case, the recommended amount of human milk avoided should be at least 90.8 L per year in order to compensate for the additional impacts due to IoT technologies implementation.

Food waste is associated with different adverse effects on the environment [56,57]. When human milk food is discarded, all inputs used in processing, transporting, preparing and storing discarded milk are also wasted. The later the milk is wasted along the chain, the greater its environmental impact, because then we also need to take into consideration the energy and natural resources expended into each of those steps. In addition, the milk discarded that ends up in wastewater treatment plants produces a large amount of greenhouse gas emissions, which impact the environment [58,59]. Human milk management also involves steps that consume diesel and fossil fuels. For instance, transporting the human milk from the donor’s home/hospital to the HMB and then from the HMB to the hospital/recipient home needs diesel and other fuels; storing the milk in the freezers and pasteurising it also uses a large amount of electricity. Wasting fuel or electricity, both in the back and front end by wasting human milk, can have an impact on the environment and exacerbates the global warming crisis with its significant carbon dioxide emissions.

Reducing and preventing human milk waste can increase food security, foster productivity and economic efficiency, promote resource and energy conservation and decrease global warming. In this scenario, the additional production of food to compensate for these losses would not be necessary. Therefore, contributing to the reduction of all downstream impacts observed during human milk handling, including transportation, storage and pasteurisation. However, further assessment to quantify the precise amount of food waste avoided is recommended.

In the second analysis (Figure 7), the influence of transportation distances on the environmental impact results was evaluated. The transportation over larger distances results in higher consumption of diesel, increasing the emissions of carbon monoxide (CO), CO_2, SO_2, NOx, NMVOCs and others. These emissions are generated due to diesel combustion, which affects mainly the impact categories of global warming, ozone formation, terrestrial ecotoxicity and fossil resource scarcity. When the transport distance is changed by 25 miles, the net impact can vary by up to 14.3% in the ozone formation (terrestrial ecosystems) impact category. Therefore, the results show that human milk transportation depends highly on the transport distance, and the milk should be collected from donors located close to the HMB, and distribution should where possible be made to local hospitals in order to decrease the environmental impacts associated with transportation.

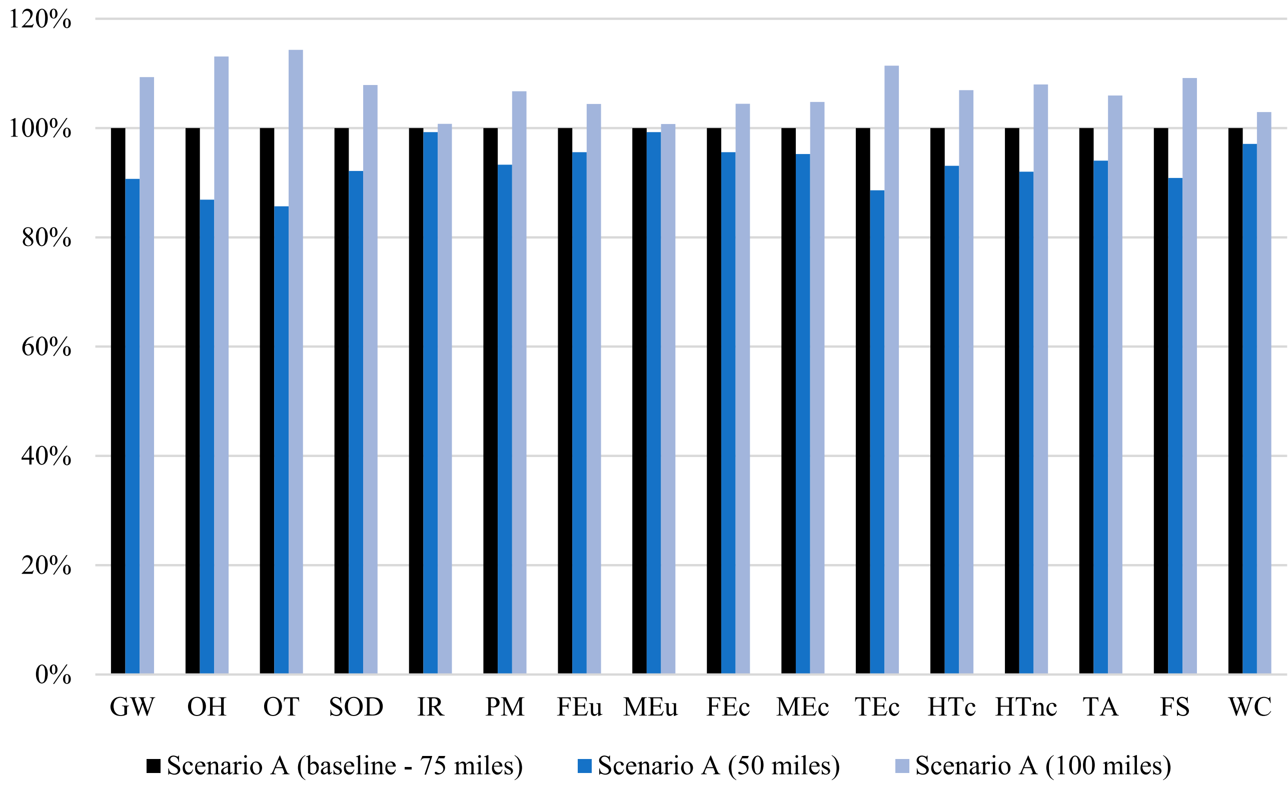

Figure 7. Results of the sensitivity analysis: effect of transportation distances.

An alternative is the introduction of more decentralised hubs, where local healthcare centres can be responsible for the collection, and the human milk bank acts as the principal organising centre supervising different branches. The creation of hubs has been designed to mitigate the impacts of having fewer milk banks and ones that collect and provide DHM over a wide area. This alternative is already in practice in this HMB. However, this study did not take into account the additional impacts associated with the creation of the additional facilities that would need to be established to allow for local collections and distributions, i.e., all the additional equipment and facility impacts and the extra staffing and other resources.

4.3. Employing Different Transport Modes in Place of Motorcycle Volunteers

The Human Milk Foundation is developing the use of drones for milk collection and delivery. While drones can substitute motorcycle volunteers in some cases, drones are sometimes the only option, especially in sparsely populated areas. Hence, an analysis of the impact of employing delivery drones has been carried out. Figure 8 shows the influence of substituting 10 % of motorcycle volunteers with delivery drones to transport human milk.

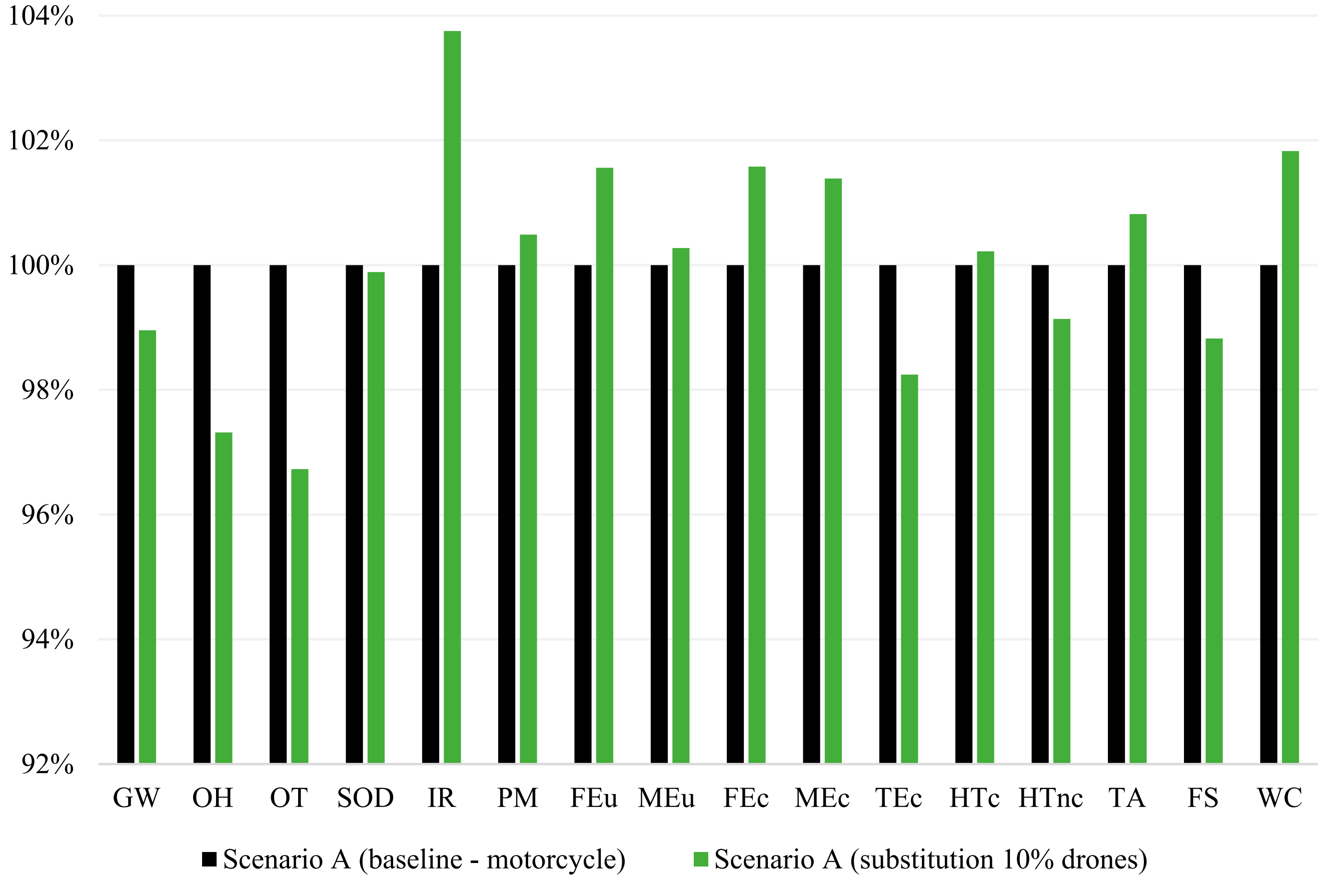

Figure 8. Results of the sensitivity analysis: effect of changing the transport mode to drones.

Effects on the environmental impacts were observed due to changes in the transportation mode. Effects on milk quality were not evaluated in this analysis. It was observed that the main categories positively affected by this substitution were global warming, ozone formation (human health and terrestrial ecosystems), terrestrial ecotoxicity, human non-carcinogenic toxicity and fossil resource scarcity. The substitution of 10% of motorcycles by drones achieved a reduction of 3.3% in ozone formation (terrestrial ecosystems). However, for other impact categories, such as ionising radiation, freshwater eutrophication, freshwater ecotoxicity, marine ecotoxicity and water consumption, this change negatively affected the environmental performance of the organisation. For the ionising radiation impact category, the environmental impact increased by 3.8%, suggesting an environmental risk from using drones due to the high electricity consumption.

From an environmental perspective, there are pros and cons to using drones for delivery services. The main expected benefit for the environment is that, compared with many traditional methods of delivery using fossil fuel, drones could reduce CO_2 emissions locally as well as other air pollutants. However, although drones avoid environmental impacts from direct diesel combustion emissions, impacts relating to additional electricity production required by a drone-based logistics system may reduce or eliminate the benefits. The impacts depend on how local power is generated, e.g., using coal or natural gas, which emit carbon pollution, versus renewable resources such as wind or solar, which do not. In 2020, the electricity supplied in the UK came from 41% fossil-fuelled power (almost all from natural gas), 46.7% zero-carbon power (including 16.1% nuclear power and 30.6% from wind, solar and hydroelectricity) and imports [60]. As environmental impacts related to electricity consumption are intrinsically linked to the electricity mix supplied in the country, successive UK governments have outlined numerous commitments to reduce fossil-fuelled power. To the extent that more renewable energy sources such as wind and solar are used to generate electricity, the total greenhouse gases associated with the use of drones could be reduced. These results can serve as a precautionary note for policymakers planning to promote the use of delivery drones due to potential environmental impact reduction.

Among significant negative environmental effects, the threat to wildlife, especially birds, is another great concern. Beyond the apparent risk of collision, birds could be affected by the noise and stress caused by the frequent presence of drones in their habitat. To date, the consequences of excessive stress caused by drones on wildlife have not been studied systematically and are little understood. Other potential environmental risks include the wastes resulting from collisions and dropped cargo and the related responsibility for their disposal. Both factors might also result in resistance from society to the widespread use of delivery drones.

Figure 9 shows the influence of substituting 10% of motorcycles with electric vehicles to transport human milk. The results show that the environmental impacts of this substitution are highly dependent on the human milk payload transported. If the average amount of human milk transported per journey is around 50 L, it was observed a positive effect for all impact categories, except ionising radiation and water consumption. The maximum reduction was achieved in ozone formation (terrestrial ecosystems), which could avoid 2.7% of the impacts.

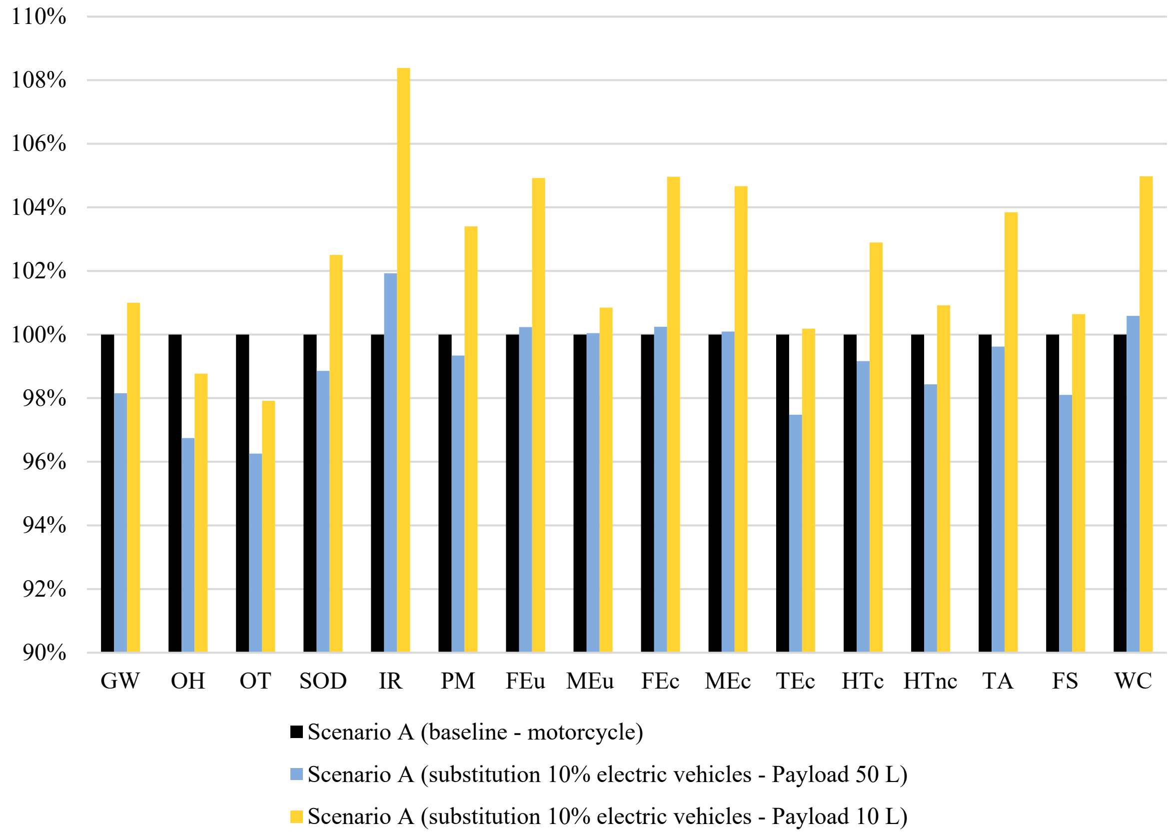

Figure 9. Results of the sensitivity analysis: effect of changing the transport mode to electric vehicles.

However, when less milk is transported per journey, and more trips are required, the environmental burden increases and a negative effect is observed for most of the impact categories. For example, the impact of ionising radiation would increase by 8.4% in this scenario. Therefore, the distribution of human milk using electric vehicles should be made transporting quantities of milk above 40 L to reduce the environmental impacts in most of the categories.

As mentioned above, battery production is an energy-intensive process. Vehicle cars rely on rechargeable batteries to run, which requires the use of energy-intensive materials such as cobalt and other metals. Producing electric vehicles leads to significantly more emissions than producing fossil fuel cars. Depending on the country of production, it can represent an additional 30 to 40% of production emissions [61].

In addition, the national electricity mix in most of the world is still powered by fossil fuels, such as coal or oil, and electric vehicles depend on that energy to get charged. The full benefits of electric vehicles will be achieved only after the electricity sources become renewable, and it might take several decades for that to happen [62]. Despite that, the local emissions per mile for electric vehicles are lower than vehicles with internal combustion engines [62], which highly affects the global warming category. However, other environmental categories should also be considered to make a more informed decision.

5. Conclusions

Quantitative estimates relating to the environmental performance of non-profit associations, such as HMBs, are crucial to provide a basis for further work on O-LCA. This methodology proved to be suitable for determining environmental impacts and savings of organisations, as the one analysed in this study, and equips decision-makers to understand the environmental performance of their companies through a comprehensive and science-based methodology.

In this study, the transportation of human milk was found as the main hotspot of this organisation for most impact categories, except ionising radiation and marine eutrophication. The electricity consumed during the second storage was the most significant contribution to the total impact of ionising radiation, while the treatment of discarded milk represented 80.7% of the impact for marine eutrophication. The strategy to integrate IoT technologies (sensors and Big Data server) to monitor temperature/humidity conditions did not adversely affect the organisation in a significant way. The batteries were responsible for a great part of the impacts of the sensors installed, followed by the printed circuit board. However, if the reduction in waste reaches 3%, then, the avoided environmental impacts resulting from this strategy could avoid 863 kg of CO_2-eq per year in the global warming category.

The sensitivity analysis regarding the influence of transport distance showed that the impacts of the HMB depend highly on the transport distance; the milk should be collected from donors located close to the HMB, and distribution should be made to local hospitals to decrease the environmental impacts associated with diesel combustion. The results of the sensitivity analysis also showed that changing part of the transportation mode from motorcycles to drones can positively affect some categories such as global warming, ozone formation, terrestrial ecotoxicity and fossil resource scarcity. However, for other impact categories, this change could result in environmental risk due to the high electricity consumption, especially for the ionising radiation impact category. Therefore, human milk logistics must be studied in a multidisciplinary way, addressing organisational, safety, economic, environmental and engineering aspects, before the transaction to a drone solution. Future studies could bring this approach to other sectors and companies. A similar analysis was performed considering the substitution by electric vehicles, and the results showed that the environmental impacts of this strategy are highly dependent on the amount of milk transported per journey. In order to reduce the environmental impacts, the amount of human milk that electric vehicles should transport in a single journey should be greater than 40 L.

While this is the first time the use of digital technologies for avoiding wasted human milk is evaluated using LCA, we are constrained by the availability of suitable data, which has limited our analysis and findings. For instance, the precise amount of food waste avoided due to IoT technologies implementation in this HMB is still under assessment, and further analysis is required. Despite these limitations, the results of this paper provide evidence of the sustainability benefits of modern digital technologies and bring out the value of investing in these technologies to support various needs of organisations. Future work should consider other difficulties associated with human milk waste, such as mothers' and donors' reduced knowledge of milk expression and saving, managerial challenges and socio-cultural and economic variables.

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Abbreviations

CFC, chlorofluorocarbons; CH4, methane; CO, carbon monoxide; Co, cobalt; CO2, carbon dioxide; Cu, copper; DCB, 1,4-dichlorobenzene; DEHP, Di(2-ethylhexyl)phthalate; DHM, donor human milk; FEc, freshwater ecotoxicity; FEu, freshwater eutrophication; FS, fossil resource scarcity; GW, Global warming; HMB, human milk banks; HTc, human carcinogenic toxicity; HTnc, human non-carcinogenic toxicity; IoT, Internet of Things; IR, ionising radiation; ISO, International Organization for Standardization; MEc, marine ecotoxicity; MEu, marine eutrophication; N_2O, Dinitrogen monoxide; NMVOCs, Non-methane volatile organic compound; NO_x, nitrogen oxides; OH, ozone formation—human health; O-LCA, Organisational Life Cycle Assessment; OT, ozone formation—terrestrial ecosystems; N, nitrogen; P, phosphorous; PCB, printed circuit board; PM, fine particulate matter formation; PM2.5, particulate matter with 2.5 m or less in diameter; SETAC, Society of Environmental Toxicology and Chemistry; SMS, short messaging service; SO2, sulphur dioxide; SOD, stratospheric ozone depletion; TA, terrestrial acidification, TEc, terrestrial ecotoxicity; TS, Technical Specifications; UNEP, United Nations Environment Programme; WC, water consumption; Zn, zinc.

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Article

A Decision Support Model for Cost-Effective Choice of Temperature-Controlled Transport of Fresh Food

Lohithaksha M. Maiyar [1,*], Ramakrishnan Ramanathan [2], Indira Roy [1] and Usha Ramanathan [3]

1 Department of Entrepreneurship and Management, Indian Institute of Technology Hyderabad, Kandi 502284, India
2 Essex Business School, University of Essex–Southend Campus, Elmer Approach, Southend-on-Sea, Essex SS1 1LW, UK
3 Nottingham Business School, Nottingham Trent University, Nottingham NG1 4FQ, UK
* Correspondence: l.maiyar@em.iith.ac.in

Abstract: The application of a plethora of wireless technologies to support real-time food quality monitoring during transportation has significantly improved the performance of fresh food delivery systems. However, deployment of these technologies increases the capital and operational costs of food delivery and, hence, not all food delivery operations need to employ them. This paper looks at the trade-off of the costs involved in utilizing these technologies with the nature of food delivered, the length of transportation, and the perceived costs of food wasted using a linear programming model. The problem is formulated over a bi-echelon network with the possibility of transporting the fresh produce through dry vans, vans with temperature control but without monitoring capability, and vans with temperature control and monitoring capability. Results indicate that under situations of infinite vehicle resource availability, the optimal choice of the van type is independent of the demand levels; however, the optimal choice changes for different travel distances and the value of penalty costs (of allowing food to go waste). For example, technologies that maintain and monitor the temperature of storage conditions will be useful for food items that quickly become waste, especially when transported over longer distances and when the penalty costs are higher.

Keywords: Internet of Things sensors; temperature control; temperature monitoring; decision support model; food waste; food supply chains

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1. Introduction

Delivering fresh food products to the end user of the right quality while adhering to perishability constraints is of foremost importance in fresh food supply chain networks. Unlike other products, the quality of perishable fresh food degrades endlessly during the downstream activities in the supply chain, leading to food-borne diseases or food wastage. According to the Centers for Disease Control and Prevention (CDC), as many as 48 million people become sick due to food-borne illnesses every year in The United states (US) alone. However, tracing back the origin of these diseases due to food contamination is challenging [1]. According to the Food and Agriculture Organization, around one-third of fresh food is wasted throughout the supply chain post-production every year [2]. This is due to poor transportation and storage facilities, as well as inadequate temperature and humidity control systems [3,4]. Several international standards, such as Hazard Analysis of Critical Control Points (HACCP), Good Agricultural Practice (GAP), and Good Manufacturing Practices (GMP) are implemented for quality assurance and a reduction in food wastage [3,5,6]. The threshold levels of temperature to safeguard food from quality damage vary depending on the type of food. For example, for frozen foods, the temperature range is between −18 and −24 °C (see [7]), while for frozen milk the range is 0–4 °C in fridges, and at or below −20 °C for long-term storage in freezers [8].

Owing to the growing need for reducing food wastage and increasing quality preservation, several food quality monitoring and control technologies that enable tracking and traceability during transportation and post-harvest storage have recently evolved [9]. These technologies range from simple Internet of Things (IoT) enabled sensors, radio frequency identification (RFID) systems, to sophisticated imaging technologies, such as spectroscopy, muti-sensor topologies, thermal imaging systems, and physics-based digital twins [4,7,9–12]. Traditional food supply chain retailers and logistics providers still depend on the use of dry vans without any temperature-controlled systems installed, usually due to the high cost of installation and maintenance of the RFID and wireless sensor network (WSN). Therefore, most of the small- and medium-sized enterprises [13,14] are unable to afford to adopt such systems despite the high level of technological maturity. Previous studies [15] have revealed that, compared to a non-temperature-controlled system, the shelf life of food can be increased by a factor of two or even three times in a temperature-controlled system. Thus, fresh food supply chain planning is seldom conducted looking at the trade-offs between the possibilities of cost reduction by preventing quality affected food losses and the increase in total supply cost due to wastage from oversupply or overstocking. However, technologies for delivering fresh food faster with optimum quality and quantity reap financial benefits and can be perceived as a strategic asset to the organization [16]. Temperature-controlled systems with monitoring capabilities are designed for automating decision-making processes during transportation. In addition to their ability to remotely monitor food safety and commodity settings, some of these systems can also control in-transit ripening and pest-management treatments [17]. To our knowledge, there is no previous research that builds integrated logistic decision models to support the right choice of transport with technology-enabled tracking and traceability for temperature-controlled systems. Our paper contributes to filling this important research gap. Accordingly, the present work focusses on addressing the following key research questions.

(i) What are the trade-offs to companies when choosing between investing in trucks with monitoring infrastructure and bearing the cost of food quality loss?
(ii) How do these trade-offs change with respect to the distance over which the food is transported and demand variations?

2. Literature Review

Temperature control refers to the capability of the refrigeration unit fitted to trucks in maintaining the pre-specified temperature, while monitoring refers to the continuous recording of this temperature using Internet of Things sensors whose outputs are made available via the Internet for further analytics, monitoring, and decision support. In this section, the first subsection discusses various technologies currently available for controlling and monitoring temperature in fresh food supply chains. The discussion in subsequent subsections is distributed into three classes of transport pertaining to temperature control and monitoring: non-temperature-controlled transport systems, temperature-controlled transport systems without monitoring capability, and temperature-controlled transport systems with monitoring capability.

2.1. Technologies Used for Quality Monitoring of Fresh Food Transportation

Several researchers have focused on developing and implementing technologies for monitoring quality. Imaging and thermography technologies have been deployed for temperature distribution studies on a pallet of fruits to evaluate and monitor food spoilage during storage using classification techniques [18–20]. Ref. [21] proposed a decision support method for quality monitoring by data acquisition from multi-sensor technologies. In any food supply chain, temperature control is essential for quality assurance and safety until consumption [22]. However, fluctuations in temperature are inevitable during the transportation and distribution of perishable foods due to their vulnerability and small inherent heat capacity [20]. Thus, most of the research on fresh food logistics primarily aims at temperature control [21]. However, a wide arena of research work exists on temperature monitoring and control using newer technologies, such as RFID, WSN, IoT, wireless networks, digital twins, and gas sensing, for improving tracking and traceability of the quality of fresh food. Ref. [22] developed a tribo-electric nanogenerator-based wireless gas sensor system for real-time spoilage marker gas monitoring.

2.2. Non-Temperature-Controlled Transport Systems

Non-temperature-controlled transport systems are low-cost dry vans which may not prevent food wastage during transit. They are relatively inexpensive transport options, but they can be used only over shorter distances because food might become bad over time. Most of the studies concerning fresh food transportation deal with this type of transport and have made efforts to perform cost optimization and inculcate sustainability while addressing perishability and quality concerns using mathematical modelling. In [23], researchers deployed a three-objective linear programming model-based food distribution planner (FDP) to minimize cost, carbon emissions, and delivery time. FDP facilitates strategic planning of food distribution by considering perishability and multi-modal transport. In [20], the researchers optimized the cost of a fast-moving consumer goods (FMCGs) distribution network using scenario analysis. Ref. [16] presented a fast-moving consumer goods network design model with a consideration of greenhouse gases and other logistic leverages. Ref. [24] proposed a bi-objective food supply chain model for minimizing total cost and carbon dioxide (CO_2) emissions for a milk distribution channel in Ireland. Ref. [25] developed a hybrid approach of mixed integer linear programming and constraint programming to examine integrated production planning and scheduling for the case of the dairy supply chain. Ref. [26] addressed the problem of van route scheduling for fresh food transportation cost optimization using an NSGA-II meta-heuristic approach. Ref. [27] presented a model for a food supply chain to study the effect of temperature and storage on product quality, costs, and sustainability of the chain.

2.3. Temperature-Controlled Transport Systems without Monitoring Capability

According to a transport economics report by USTDA (2000), temperature-controlled systems or reefer vehicles can be more than twice as expensive as the traditional dry vans if purchased, although the cost might have reduced in the last two decades [28]. The temperature-controlled transport systems are advantageous in the sense that they can keep food produce fresh, thereby causing them to be transported over longer distances. However, these vans do not have the functionality of generating sufficient data for predictive modelling and informed decision making. If these transport systems do not have monitoring capability (in other words the temperature readings are not made available over the Internet for continuous monitoring), then there is some chance that the temperature control system fails and is detected only at the end of the journey. By this time, it would be too late to take any corrective action, and the entire food consignment would be wasted.

Quality and perishability concerns in fresh food transportation can still be addressed by installing temperature-controlled systems without the capability for monitoring. Various researchers have developed and utilized such technologies for dynamic shelf life determination and temperature control. Due to lack of remote and automatic control mechanisms, these systems fail to assist in the decision-making process in the event of disruptions and uncertainties [9] in real time; however, are useful for generating offline data and providing a route for retrospection. Post-harvest food loss management was given a fresh perspective by [29] in terms of studying technology adoption barriers and by conducting a feasibility study for the successful implementation of various temperature control technologies. Ref. [30] proposed a multi-temperature joint distribution (MTJD) for better handling temperature-sensitive food. The use of cold cabins and eutectic plates was adopted for operational cost reduction and to ensure food quality and safety during transportation. Ref. [20] developed an integrated critical temperature indicator (CTI)-RFID for maintaining the fresh cut fruit supply chain within the temperature range of 18–19 °C. Ref. [31] have developed a load-dependent vehicle routing model for optimal route decisions after accounting for emissions from the refrigeration system. Similarly, [32] have discussed the scope of IoT based systems to support food supply chains and suggested that simulation gaming could provide promise for studying the system in detail. Furthermore, [33] have developed a mixed-integer network flow model that considers the rates of product quality decay of heterogeneous food products.

2.4. Temperature-Controlled Transport Systems with Monitoring Capability

An efficient cold chain logistics requires an automated temperature monitoring and controlling facility during transportation. Such a system can not only maintain appropriate temperatures to keep food produce fresh for longer but can also transport the produce over longer distance and, at the same time, provide confidence that the produce will arrive at the destination still fresh. The main advantage of temperature control and monitoring is that in case that the temperature control mechanism fails while the truck is in transit, the failure is rapidly identified, and corrective actions can be taken to preserve the quality of food, thereby minimizing the chance of it becoming waste. However, the downside is this would incur additional costs for installing and maintaining technologies to monitor and send alerts to decision-makers rapidly. These costs are slowly coming down as more and more companies are starting to use such advanced systems.

During the last decade, the use of IoT-based sensors for food quality monitoring and tracking temperature has become more and more operational in cold chain fresh food logistics. Furthermore, it is of great use to automate the decision-making process during transit. Numerous works have focused on developing and adopting these technologies. Ref. [34] utilized Electronic Product Code Information Services (EPCIS)-based online monitoring and a time–temperature maintenance system in a cold meat chain. This helped to decrease the losses caused due to temperature fluctuations. Similarly, [35] developed a real-time monitoring system based on RFID to improve the efficiency of a perishable goods delivery system. Additionally, it provides warnings when temperature, humidity, or any other environmental condition goes beyond safety limits. Ref. [35] proposed an "Intelligent Container", which tracks and traces the temperature history and monitors the perishable food quality. Ref. [4] approached the problem of delivering perishable goods using wireless sensor node-based temperature control systems and proposed a smart cold chain management system. This framework enabled offline as well as online tracking and traceability through data centralization. Ref. [36] proposed an intelligent container-based framework for the shelf life prediction and remote monitoring of fresh food during transportation. Ref. [37] used RFID-based technology to gauge the quality and control the temperature in real-time throughout the supply chain. Ref. [38] introduced a real-time monitoring system based on the ZigBee standard, which sensed various environmental parameters, such as temperature, CO_2, humidity, vibrations, etc. Ref. [12] proposed a real-time smartphone-based monitoring system to ensure the quality and safety of food products. The system considers parameters, such as temperature, humidity, and location during transportation. Ref. [39] proposed an intelligent distribution strategy for perishable food considering the destination hub's shelf life, transit time, and consumption rate. According to this strategy, pallets with low shelf life are transported to the destination with high proximity and a higher consumption rate and vice-versa. Ref. [40] proposed a methodology based on sensory and chemical attributes to predict and monitor the shelf life of perishables. Ref. [41] demonstrated an automatic freshness/quality monitoring and controlling tool based on predictive data transmission technology. The work also showed that the use of such technologies helps to reduce transportation costs. Ref. [42] proposed data-driven traceability tool highlighting the impact of logistics operations on fresh food.

From the above literature, it is observed that several attempts have been made to improve the quality of fresh food using temperature-controlled systems as well as temperature-controlled systems with monitoring capability. Although cost concerns are evident from the reported literature, the existing work does not focus on developing a cost-effective model or address the dilemma of choosing the appropriate type of van for the transportation of fresh food. This paper aims to fill this important research gap by building a model which would help retailers to choose between the vans while maintaining the economic feasibility and focusing on reductions in fresh food wastage. Thus, the underpinning contributions of this work are two-fold. First, it evaluates how the trade-off based on cost of transportation and quality of fresh food to be delivered to customers affect the retailer's choice of transport. Secondly, it considers how these trade-offs change with range of distances and demand to achieve optimal conditions.

3. Problem Description and Mathematical Modelling

Despite the rising development of automated technologies for food quality monitoring, most of the retailers and logistic providers resist investing in temperature-controlled vans with full monitoring capability. This is due to the perceived high costs of installation and maintenance associated with temperature-controlled vans in comparison to dry vans. While using dry vans may initially look cost effective from a retailer's point of view, the high rate of quality degradation and fresh food wastage might result in a negative economic and environmental impact. That being the case, retailers are often subjected to a dilemma in choosing the appropriate type of van for the transportation of fresh food which is not only cost-effective but also helps to reduce fresh food wastage. In addition, the growing concern about the sustainability impacts of food waste [43] and increased awareness of the need to reduce food waste (for example, Europe's resolve to reduce food waste by half in 2030, see [44]) mean that the social and environmental costs of food waste might become more visible to companies as penalty costs in the long run. Hence, the perception of optimal transportation option may need to change depending on the importance associated with food waste (captured via a penalty cost) and the distance travelled. In this paper, an integrated food quality driven logistics decision support model (M) is proposed as a linear programming problem for finding out the optimal transport plan under the possibility of transporting fresh food in different type of vans associated with different levels of quality monitoring technologies. For simplicity, the proposed model M uses the following assumptions.

- The model considers one distinct type of fresh produce.
- All demands and availability of fresh produce at each producer and retailer are deterministic.
- Transportation of fresh produce is by road.
- The transportation takes place within a single time period.

The notations for the decision variable and parameters used in problem formulation are described in Table 1.

Table 1. Notations for parameters and the decision variable.

Sets	
i	Set of producers $i_1, i_2 \ldots, i_n$
j	Set of retailers $j_1, j_2 \ldots, j_n$
k	Set of van types $\{k_1, k_2, k_3\}$ • k_1 represents dry vans with no temperature control system and no monitoring capability. • k_2 represents temperature-controlled vans without monitoring capability. • k_3 represents temperature-controlled vans with monitoring capability
Decision Variable	
x_{ijk}	Quantity of fresh produce transported between producers to retailers using k type of van (kg.)

Table 1. *Cont.*

Parameters	
f_k	Fixed cost per unit quantity for hiring k type of van (EUR/kg)
c_{ijk}	Variable cost per unit quantity per unit distance from i to j using k type of van (EUR/kg-km)
p_k	Cost of fresh food loss associated with quality loss per unit quantity for k type of van (EUR/kg)
d_{ij}	Distance between producers and retailers (km)
d_k	Maximum distance k type of van can travel from the producers to retailers without any loss in quality of fresh produce (km)
A_i	Availability of fresh of fresh produce at the producers (kg)
D_j	Demand at the retailers (kg)
$ss_.$	Shelf life (h)
ss_{ek}	Improved shelf life using k type of van in hours (h) $ss_{ek} = ss(1 + \alpha_k)$ Where α represents the shelf life improvement factor associated with k type of van
z_{ijk}	Binary parameter which takes the value 1 for $d_{ij} > d_k$ and 0 otherwise
r_k	Quality loss factor associated with k type of van

Objective Function,

$$\text{Minimize Z } = \sum_{k\in K} f_k \sum_{i\in I}\sum_{j\in J} x_{ijk} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk}x_{ijk}d_{ij} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} p_k z_{ijk} r_k x_{ijk} \tag{1}$$

The model aims to minimize the total cost of transport including quality loss cost with key decisions to evaluate the optimal quantity of produce that will need to be transported from producers to retailers, the transportation route, and the type of van to be chosen for the route to transport the required quantity. Equation (1) represents the objective function constituting the summation of the total fixed cost of hiring each type of van used between producer–retailer links, variable transportation cost, and total cost for fresh food loss. The total cost of fresh food loss is estimated by multiplying the penalty incurred for losing a unit quantity of food with the total amount of food lost. The amount of food lost for a given combination of origin node, destination node, and van type are calculated by the term $r_k x_{ijk}$, and is added to the total food loss quantity if and only if there is a food loss for the distance (d_{ij}) travelled. This is ensured by the activation of $z_{ijk} \in \{0, 1\}$, which takes a value of 1 whenever the distance between two nodes (d_{ij}) is greater than the threshold distance (d_k). The given objective function is constrained to meet the demand at each retailer node, as shown in Equation (2), subject to the availability of food quantity at each producer, as represented in Equation (3). Equation (4) represents the non-negativity constraints for each decision variable.

The constraints are as follows.

Demand constraint:

$$\sum_{i\in I}\sum_{k\in K} x_{ijk}(1 - r_k z_{ijk}) \geq D_j \qquad \forall j \tag{2}$$

$$where,\ z_{ijk} = 1\ \forall\ d_{ij} > d_k$$

$$d_k = Avg.\ speed\ of\ van \times ss(1 + \alpha_k)$$

Capacity constraint:

$$\sum_{j\in J}\sum_{k\in K} x_{ijk} \leq A_i\ \forall i \tag{3}$$

Non-negativity constraints:

$$x_{ijk} \geq 0 \qquad \forall i, \forall j, \forall k \tag{4}$$

Equation (2) ensures the demand at each retailer node is met after considering the occurrence of fresh food loss, if any, for a given type of transport van. Each type of van is associated with a loss factor of $r_k \in (0, 1)$. We assume that r_k is the lowest for temperature-controlled vans with full monitoring capability and highest for dry vans. The binary parameter $z_{ijk} \in \{0, 1\}$ is defined by comparing the actual distance between the producer–retailer pair and threshold distance each type of van can travel without any quality loss, bearing in mind the possible extension of shelf life (ss) with an improvement factor of $\alpha \in (0, 1)$. The value of α is zero for dry vans and highest for the temperature-controlled vans with full monitoring capability. In this paper, the shelf life is taken as the difference between primary shelf life and display shelf life in order to ensure that the food remains at the right quality while it reaches the retailer. Primary shelf life is the time period from the point of harvest to the point the fresh produce becomes unacceptable, whereas display shelf life is the time for which fresh produce can be stored under specific conditions of store display [45].

4. Data and Experiments

The fresh food transportation problem is articulated in the context of a north-western European-based fresh food supply chain where different types of fresh food are transported from the producers to the retailers. While transporting the food, temperature-controlled systems with monitoring capability increases the potential of decreasing the perishability rate of fresh food, thereby reducing food wastage. Therefore, the food company has three options to transport their fresh food, namely dry vans with no temperature monitoring and control, temperature-controlled vans with no quality monitoring capability, and temperature-controlled vans with quality monitoring capability, as shown in Figure 1. Multiple combinations of various parameters are used to solve the model for different instances. These parameter values are shown in Table 2.

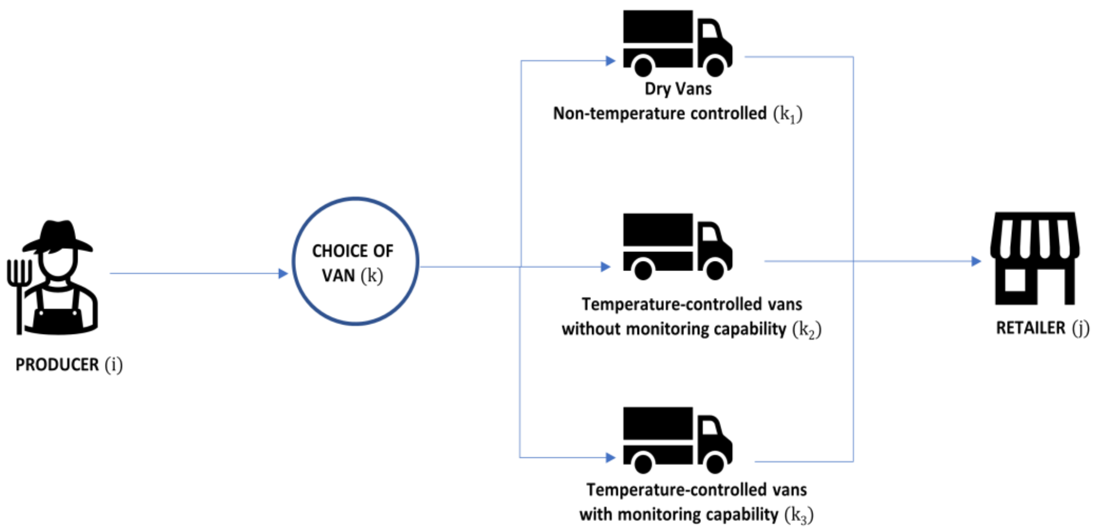

Figure 1. Fresh food supply network with different transport types.

The model was solved with CPLEX solver in a Pyomo Python 3.1 environment using an Intel(R) Core (TM) i5-10400 CPU, 2.90GHz processor, and 16 GB RAM. Results obtained for the low and high demand instances with low unit penalty cost of quality loss are described in Tables 3 and 4, respectively. Table 5 describes the results for a case of high demand instance with high penalty cost for quality loss.

Table 2. Parameters for the case of mixed configuration of distances ($d_{ij} \in N$) [17,22,30].

Parameter	Description	Value
f_k	Fixed cost per unit quantity for hiring k type of van	$f_{k1} = 0.102$ EUR/kg $f_{k2} = 0.14$ EUR/kg $f_{k3} = 0.16$ EUR/kg
c_{ijk}	Variable cost per unit quantity per unit distance from i to j using k type of van	$c_{k1} = 0.01$ EUR/kgkm $c_{k2} = 0.012$ EUR/kgkm $c_{k3} = 0.013$ EUR/kgkm
p_k	Cost associated with quality loss per unit quantity for van type k	$p_k = 0.5$ EUR/kg (low) $p_k = 5$ EUR/kg (high)
d_{ij}	Distance between producer i and retailer j	280–1520km
d_k	The maximum distance a k type of van can travel from producers to retailers without any loss in quality of fresh produce	$d_{k1} = 540$km $d_{k2} = 756$km $d_{k3} = 756$km
A_i	Availability of fresh produce at the producers	1500 kg $\forall i$ $(low\ demand\ instance)$ 15,000 kg $\forall$ $(high\ instance)$
r_k	Quality loss factor associated with k type of van	$r_{k1} = 0.5$ $r_{k2} = 0.2$ $r_{k3} = 0.15$
D_j	Demand at supermarket	1000 kg $\forall j$ $(smaller\ instance)$ 10,000 kg $\forall j$ $(larger\ instance)$
$ss_.$	Shelf life	18 h

Table 3. Results obtained for low demand and low unit penalty cost instance with mixed travel distances.

Objective function value	EUR 82,631.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P1,R4)	k_2	750	920
	(P2, R6)	k_2	1000	670
	(P2, R8)	k_2	500	701
	(P3, R7)	k_2	500	650
	(P3, R9)	k_1	1000	510
	(P4, R7)	k_2	625	850
	(P5, R2)	k_2	500	620
	(P5, R3)	k_2	1000	600
	(P6, R10)	k_2	1000	700
	(P6, R8)	k_2	500	701
	(P7, R4)	k_2	500	770
	(P7, R5)	k_2	1000	700
	(P8, R1)	k_1	1000	430
	(P8,R2)	k_2	500	720

Table 4. Results obtained for high demand instance with mixed travel distances.

Objective function value	EUR 826,310.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P1,R4)	k_2	7500	920
	(P2, R6)	k_2	10,000	670
	(P2, R8)	k_2	5000	701
	(P3, R7)	k_2	5000	650
	(P3, R9)	k_1	10,000	510
	(P4, R7)	k_2	6250	850
	(P5, R2)	k_2	5000	620
	(P5, R3)	k_2	10,000	600
	(P6, R10)	k_2	10,000	700
	(P6, R8)	k_2	5000	701
	(P7, R4)	k_2	5000	770
	(P7, R5)	k_2	10,000	700
	(P8, R1)	k_1	10,000	430
	(P8,R2)	k_2	5000	720

Table 5. Results obtained for high demand instance and high unit penalty cost (5 EUR/kg) with mixed travel distances.

Objective function value	EUR 841,074.70			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P1,R4)	k_3	6764.705	920
	(P1,R7)	k_3	5882.35	850
	(P2, R6)	k_2	10,000	670
	(P2, R8)	k_2	5000	701
	(P3, R7)	k_2	5000	650
	(P3, R9)	k_1	10,000	510
	(P4, R2)	k_2	5000	720
	(P5, R2)	k_2	5000	620
	(P5, R3)	k_2	10,000	600
	(P6, R10)	k_2	10,000	700
	(P6, R8)	k_2	5000	701
	(P7, R4)	k_2	5000	770
	(P7, R5)	k_2	10,000	700
	(P8, R1)	k_1	10,000	430

It is observed that for producers with high proximity to the retailers ($d_{ij} \leq d_{k_1}$), the dry van is chosen, and $z_{ijk_1} = 0$, indicating no quality loss. However, as the distance increases beyond d_{k_1} or for those corresponding transport segments which have transport distances greater than the dry van threshold transport distance to incur food loss (d_{k_1}), the set of z_{ijk_1} type of variables take a unity value.

Hence, for retailers at low proximity from producers ($d_{ij} > d_{k_1}$) a trade-off between temperature-controlled vans and temperature-controlled vans with full monitoring capability is observed. The results suggest that the decision on the choice of a particular type of van is independent of the demand level.

The data and results presented in Tables 3–5 show very interesting trade-offs in the decision on optimal transportation choice for the fresh food supply chain. The results are discussed via three theorems, as seen below.

Theorem 1. *For a given problem of type M, with short distances over which there is no perceptible change in food quality, dry vans without temperature monitoring and control systems are the optimal choice.*

Proof. Please see Appendix A.1. □

For distances $d_{ij} < d_{k_1}$, given that $d_{k_1} < d_{k_2}$ and d_{k_3}, this implies $d_{k_1} < d_{k_2}$ and d_{k_3}. This indicates that $z_{ijk} = 0$, which suggests that irrespective of the vans chosen, the fresh food quality loss or fresh food wastage does not occur in this case. Hence, the cost for quality loss and fresh food wastage becomes zero $\forall k$. Now, the decision on choice of van is solely dependent on the fixed and variable transportation cost. It is also known that fixed hiring costs for different types of vans are related, as $f_{k_1} < f_{k_2} < f_{k_3}$. Furthermore, variable costs of transport per unit distance per unit quantity for different van types are interrelated as $c_{k_1} < c_{k_2} < c_{k_3}$. Therefore, transport using dry vans becomes the best choice because the total cost of transportation is lowest for this case. This is illustrated for a simple case of one producer and one retailer, as seen in Figure 2, which clearly shows the difference in cost of transportation through each type of van with the total objective function value being the least for dry vans. Additionally, for the case of 8 producers and 10 retailers with a demand of 10,000 kg at each sink node, dry vans are chosen to achieve the optimum, as shown in Table 6.

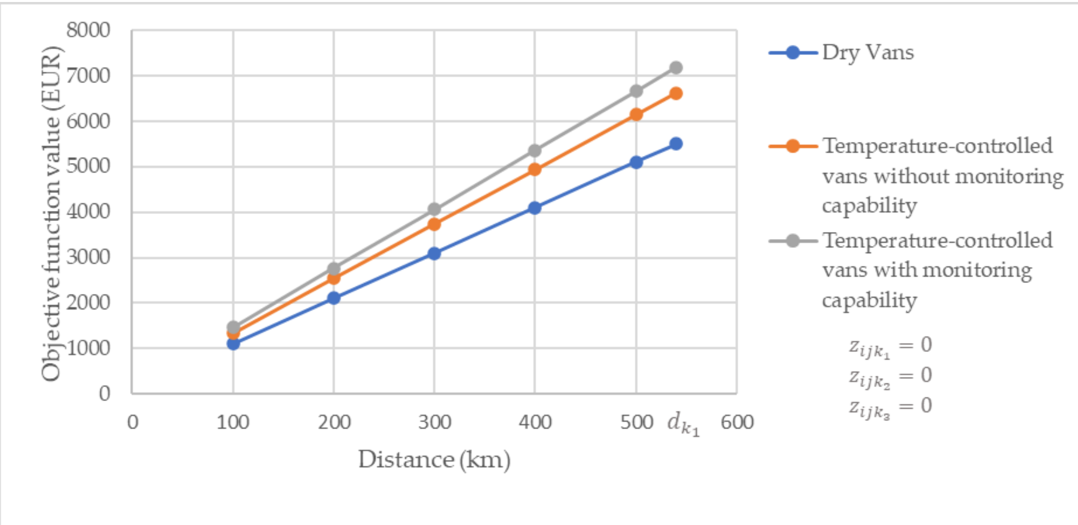

Figure 2. Change in total cost of transportation with cost of fresh food loss with increasing distance for the case of one producer and one retailer pair with demand D_j = 10,000 kg and distance $d_{ij} \leq d_{k_1}$.

Theorem 2. *For a given problem of type M, with medium range distances over which freshness of the food can be maintained with appropriate temperature control, temperature-controlled vans without monitoring capability are the optimal choice.*

Proof. Please see Appendix A.2. □

Table 6. Results obtained for the case of short distances $d_{ij} \leq d_{k_1}$.

Objective function value	EUR 3,224,150.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P1, R1)	k_1	10,000	210
	(P1, R3)	k_1	5000	130
	(P2, R4)	k_1	5000	180
	(P2, R7)	k_1	10,000	150
	(P3, R4)	k_1	5000	210
	(P4, R3)	k_1	5000	300
	(P4, R8)	k_1	10,000	101
	(P5,R10)	k_1	10,000	250
	(P5,R6)	k_1	5000	270
	(P6,R2)	k_1	10,000	320
	(P6,R5)	k_1	5000	300
	(P7,R6)	k_1	5000	107
	(P7,R9)	k_1	10,000	210
	(P8,R5)	k_1	5000	300

When distances d_{ij} are between $d_{k_1} and\ d_{k_2}$, $z_{ijk_1} = 1$ for dry vans, while for temperature-controlled vans with or without monitoring capability, $z_{ijk_{2,3}} = 0$, which means if dry vans are chosen, it would lead to quality loss and fresh food wastage with the loss factor of r_{k_1}. Hence, with each quantity transported through dry vans, in addition to the increase in variable transportation cost, the cost of fresh food loss also increases. Furthermore, to satisfy the demand, extra quantities with a factor of $\left(\frac{1}{1-r_k}\right)$ must be transported to compensate for the lost quantities. As r_k is highest for dry vans, the cost of fresh food loss increases steeply, as observed in Figure 3, and it becomes economically impractical to choose dry vans for travel distances beyond d_{k_1}. The choice between temperature-controlled vans with monitoring capability and without monitoring capability is dependent only on the minimum total of fixed and variable transportation cost, as neither would lead to quality loss when $d_{ij} \in \left(d_{k_1}, d_{k_2}\right]$. With the cost of transportation being lower for temperature-controlled vans without monitoring capability, they become the optimum choice. This can also be observed from Figure 3 for the illustrated case of one producer and one retailer. Furthermore, the results obtained for another case of 8 producers and 10 retailers are described in Table 7, where again the optimal choice of k_2 type of vans is showcased.

Theorem 3. *For a given problem of type M, and $d_{ij} > d_{k_{2,3}}$, and unit penalty cost for quality lossp, the optimal choice of transport changes from temperature-controlled vans without monitoring capability to temperature-controlled vans with monitoring capability when the unit penalty cost exceeds* $\left[\left(\left(\frac{1-r_{k_2}}{\Delta r_{23}}\right)\left(\Delta f_{23} + \Delta c_{23} d_{ij}\right)\right) - \left(f_{k_2} + c_{k_2} d_{ij}\right)\right]$.

Proof. Please see Appendix A.3. □

In this case, the travel distances are such that $d_{ij} > d_{k_{2,3}}$, and non-dry vans also incur fresh food quality loss and fresh food wastage. As $d_{k_3} = d_{k_2} > d_{k_1}$, the parameter $z_{ijk} = 1$ for all d_{ij} and for each k. Hence, in this case, irrespective of the type of van chosen, fresh food quality degrades, leading to fresh food wastage. From Theorem 2, it is proved that in such cases dry vans incur huge amount of fresh food loss and, hence, are not viable. The trade-off between the k_2 and k_3 types of vans is made based on unit penalty cost for quality loss. p is defined in Table 1 as the cost of fresh food loss associated with quality loss per unit food quantity for k type of van (EUR/kg). However, this value can be interpreted practically for a company as the loss of revenue for the food wasted. However, food waste is associated with significant environmental and social costs, especially when it ends up in landfill where it emits greenhouse gases. In addition, food wastage also means wasted resources (such as water, electricity, labor, and fertilizers) that went into the production of the food, which were also involved in the emission of greenhouse gases. If food waste is avoided and the saved food is used to feed those in need, it could also result in reduced poverty and, consequently, crime rates. This can be interpreted as one of the social costs of food waste. In order to internalize the social and environmental costs, governments across the world are making policy changes in the form of regulatory charges. Hence, the costs of food waste could be much higher than the value of the private cost perceived by a single food firm.

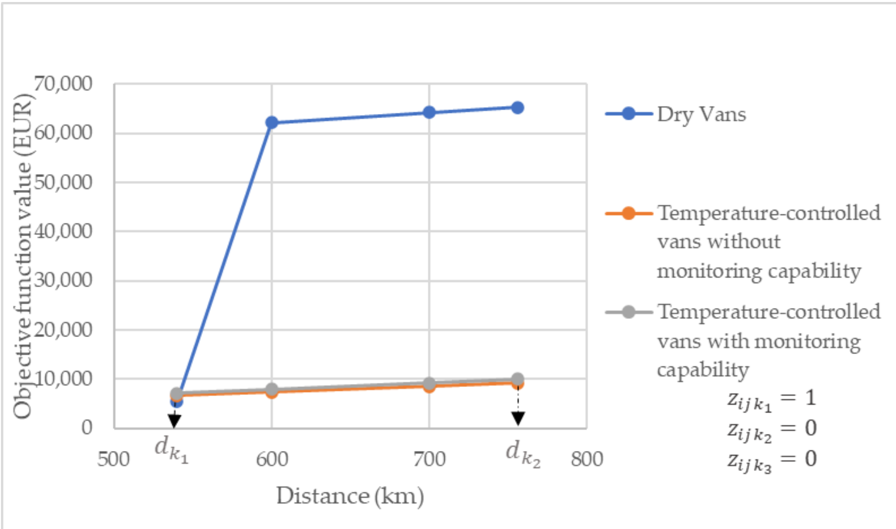

Figure 3. Change in total cost of transportation with cost of fresh food loss with increasing distance for the case of one producer and one retailer pair with demand D_j = 10,000 kg and distance $d_{ij} \in (d_{k_1}, d_{k_2}]$.

Table 7. Results obtained for the case of distances $d_{ij} \in (d_{k_1}, d_{k_2}]$.

Objective function value	EUR 738,320.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P1, R5)	k_2	5000	580
	(P1, R9)	k_2	10,000	610
	(P2, R6)	k_2	5000	670
	(P2, R7)	k_2	10,000	550
	(P3, R3)	k_2	10,000	570
	(P3, R5)	k_2	5000	550
	(P4, R1)	k_2	10,000	630
	(P4,R2)	k_2	5000	620
	(P5,R2)	k_2	5000	620
	(P5,R8)	k_2	10,000	601
	(P7,R4)	k_2	10,000	670
	(P8,R10)	k_2	10,000	550
	(P8,R6)	k_2	5000	670

Considering the importance of fresh food loss from economic, environmental, and social perspectives, it is important to know the trade-off point of the unit penalty cost at which the retailers prioritize preventing fresh food loss with an appropriate choice of vans. We arrive at this threshold penalty cost looking at the decrease in the total cost of transportation (including fixed hiring cost, variable transportation cost, and quality loss cost) for temperature-controlled vans with monitoring capability in comparison to temperature-controlled vans without monitoring capability at the threshold point. The detailed explanation for this reduction in total cost of transportation for the third category of vans is explained in Appendix A.3. This can be observed for the case of one producer and one retailer, as shown in Figure 4. Furthermore, Tables 8 and 9 showcase this shift in the choice of vans from temperature-controlled vans without monitoring capability to temperature-controlled vans with monitoring capability with the increase in unit penalty cost, respectively, for a case of 8 producer and 10 retailers.

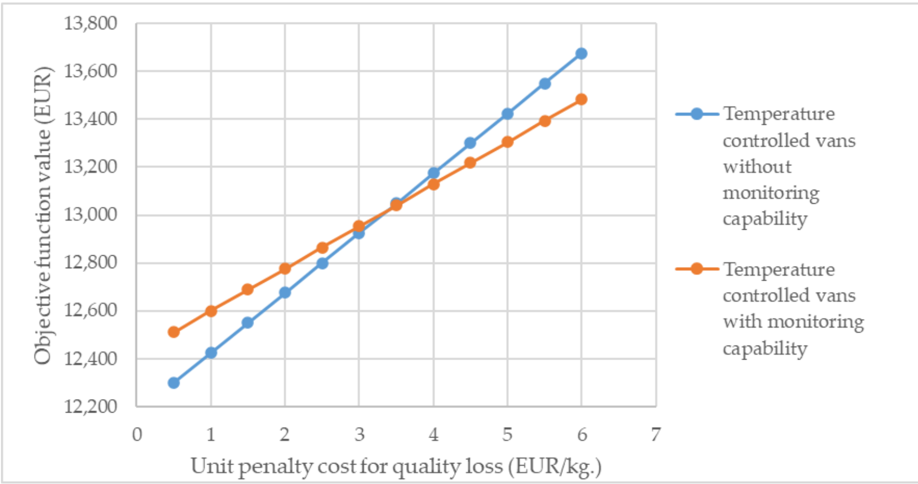

Figure 4. Change in total cost of transportation with cost of fresh food loss with increasing unit penalty cost for the case of one producer and one retailer pair with demand D_j = 10,000 kg and distance $d_{ij} > d_{k_{2,3}}$.

Table 8. Results obtained for the case of long distances $d_{ij} > d_{k_3} = d_{k_2}$, high demand, and unlimited availability with low unit penalty cost.

Objective function value	EUR 1,201,650.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P3, R3)	k_2	12,500	930
	(P5, R5)	k_2	12,500	800
	(P5, R8)	k_2	12,500	901
	(P6, R10)	k_2	12,500	800
	(P6, R6)	k_2	12,500	770
	(P6, R7)	k_2	12,500	760
	(P6, R9)	k_2	12,500	790
	(P7,R1)	k_2	12,500	780
	(P7,R2)	k_2	12,500	770
	(P7,R4)	k_3	12,500	770

Table 9. Results obtained for the case of long travel distances $d_{ij} > d_{k_3} = d_{k_2}$, high demand, unlimited availability, and with low unit penalty cost.

Objective function value	EUR 1,201,650.0			
Number of variables	481			
Number of constraints	249			
	Route (i,j)	Choice of van (k)	Quantity of fresh produce transported x_{ijk} (kg)	Distance between (i,j) d_{ij} (km)
Fresh produce transported from i^{th} producer to j^{th} retailer using van type k	(P3, R3)	k_3	11,764.705	770
	(P5, R5)	k_3	11,764.705	800
	(P5, R8)	k_3	11,764.705	801
	(P6, R10)	k_3	11,764.705	800
	(P6, R6)	k_3	11,764.705	770
	(P6, R7)	k_3	11,764.705	770
	(P6, R9)	k_3	11,764.705	760
	(P7,R1)	k_3	11,764.705	790
	(P7,R2)	k_3	11,764.705	780
	(P6,R4)	k_3	11,764.705	770

Sensitivity Analysis for Different Types of Perishables

For the purpose of understanding the behavior of the proposed model for the transport of different fresh food types, a classification of fresh foods based on their perishable nature, temperature and humidity requirements, and ethylene sensitivity is carried out, as shown in Table 10. According to the study conducted by [46], some fresh foods, such as apples and cabbages, may have the same ideal temperature and relative humidity requirements but are placed in two different categories due to difference in their ethylene sensitivity levels. For example, fruits, such as apples, cherries, and berries produce high levels of ethylene which leads to discoloration, softening, and bitterness of ethylene sensitive crops, thereby reducing their shelf life. Furthermore, products, such as onions and garlics may disseminate off-flavors to odor sensitive fruits and vegetables, such as apples and potatoes. The majority of fruits have high relative humidity requirements due to the high water content in them, while onions and garlic would decay in the presence of high humidity.

Considering the varied nature of each food type, sensitivity analysis is performed over each perishable food type. One distinct fresh food from each type was selected and was solved for two instances—for the 1 producer and 1 retailer case, as illustrated in Figure 5a–e, and for the 37 producers and 37 retailers' case, as described in Table 10. From the results obtained it can be inferred that for the perishable types 1 and 3 which have a long shelf life of up to 3–4 weeks with adequate temperature control, a combination of dry vans and temperature-controlled vans is optimal considering the distances spanning from 46–4508 km between the major European cities. The trade-off between temperature-controlled vans and temperature-controlled vans with monitoring capability for fresh food with high perishability (type 2, type 5, and type 6) is made at the penalty cost of quality loss, as elucidated in Theorem 3. For type 3 perishables, the importance of using temperature-controlled vans with monitoring capability to prevent fresh food loss is realized at a penalty cost as low as EUR 1.716, while for type 5 and type 6 it is realized at a penalty cost greater than EUR 4.89 and EUR 6.9, respectively. Type 3 perishables, such as cranberries, may be transported using temperature-controlled vans, as fresh food loss can be prevented to a greater extent by maintaining adequate temperature. This can also be observed in Figure 5d, where the total cost of transportation using temperature-controlled vans is considerably lower in comparison to temperature-controlled vans with monitoring capability and dry vans throughout the sample distance range. Wise use of temperature-controlled vans for transporting selective fresh vegetables and fruits can help reduce food waste, which indirectly helps green logistics and distribution.

Table 10. Results obtained for sensitivity analysis for a high instance case for different perishable types with high demand, unlimited availability, and high unit penalty cost.

	Perishable Type 1	**Perishable Type 2**	**Perishable Type 3**	**Perishable Type 4**	**Perishable Type 5**	**Perishable Type 6**
Fresh food	Apples, apricots, berries, cherries, grapes, pears	Lettuce, bok choy, celery, strawberry, spinach, parsley	Garlic, onion, shallots	Cranberries, lemons, oranges, lychees, tangerines	Potatoes, beans, okra, eggplant	Guavas, papayas, bananas, pineapple, pumpkins
Temperature requirements	0–2.23 °C	0–2.23 °C	0–2.23 °C	4.50 °C	10 °C	12.7–15.5 °C
Relative humidity requirements	90–95%	90–95%	65–75%	90–95%	90–95%	85–90%
Selected Perishable for analysis	Apples	Strawberries	Onions	Cranberries	Eggplants	Bananas
Number of variables	8215	8215	8215	8215	8215	8215
Number of constraints	4145	4145	4145	4145	4145	4145
Objective function value (EUR)	EUR 1,048,940	EUR 1,367,101.76	EUR 1,048,940.	EUR 1,087,040	EUR 1,208,005	EUR 1,157,745
Prominent choice of vehicle	k_1 and k_2	k_3 for $p >$ EUR 1.716 and k_2 for $p \leq$ EUR 1.716	k_1 and k_2	k_2	k_3 for $p >$ EUR 4.98 and k_2 for $p \leq$ EUR 4.98	k_3 for $p >$ EUR 6.9 and k_2 for $p \leq$ EUR 6.9

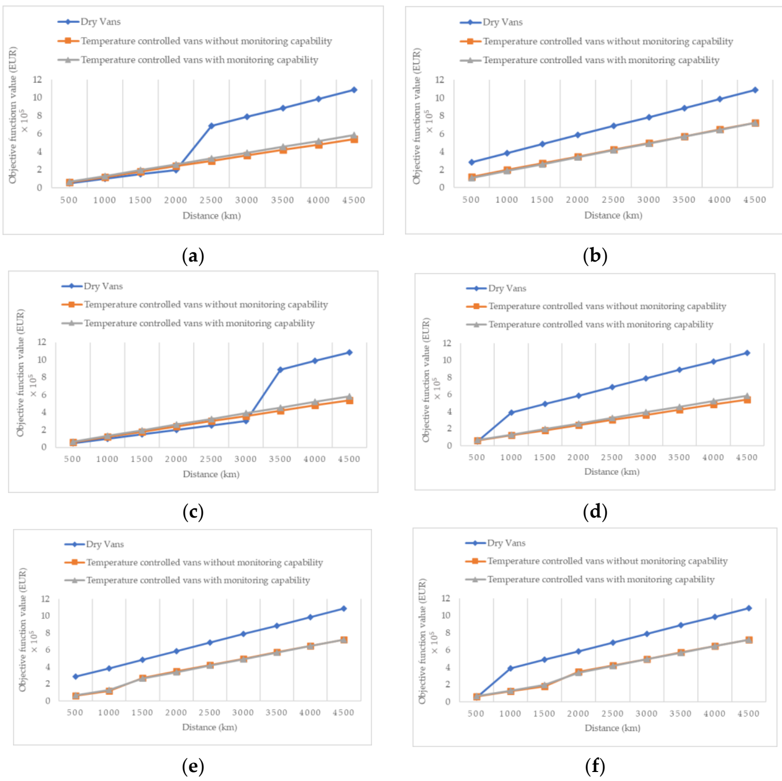

Figure 5. Change in total cost of transportation with cost of fresh food loss for the case of one producer and one retailer pair with demand D_j = 10,000 kg and increasing distance for (**a**) perishable type 1 (apples); (**b**) perishable type 2 (strawberries); (**c**) perishable type 3 (onions); (**d**) perishable type 4 (cranberries); (**e**) perishable type 5 (eggplants); (**f**) perishable type 6 (bananas).

5. Discussion

Based on the validation of the proposed model on several instances in the previous section and the theorems elicited therein, effective strategies for choosing the appropriate van types for fresh food transportation have been derived. To summarize, for shorter distances, fresh food transport through dry vans is the optimal choice. This is because of the deteriorating effect of temperature and humidity on the fresh food quality, leading to fresh food wastage which does not kick in within the delivery time window. Hence, it is viable for retailers with high proximity to producers to opt for dry vans. It is important to note that, to prevent further decay of fresh food items, especially with high perishability rates, an adequate temperature-controlled environment must be made available at the store. As the travel distance increases, more time is needed to transport fresh food; therefore, the choice of vans shifts from dry vans towards non-dry vans.

Given that the quantity loss factor for temperature-controlled vans with monitoring capability is the lowest, the fresh food wastage is lowest for them at any given instance. Therefore, the temperature-controlled vans with monitoring capability become the optimal choice of transport when the penalty cost of quality loss is taken into consideration from economic, environmental, and social perspectives, in spite of their higher cost of hiring. This observation will be helpful for larger supplier–retailer travel distances for planning efficient last mile deliveries. This will help the retailers to enhance their services by providing optimal quality fresh food to customers, leading to an increase in their goodwill. Furthermore, Theorem 3 proves that temperature-controlled vans with monitoring capability gain more advantage for longer travel distances over dry vans, in addition to having the benefit of lesser costs of fresh food loss. For a given range of distance $d_{ij} \in \left(d_{k_1}, d_{k_{2,3}}\right]$, temperature-controlled vans without monitoring capability are viable. Although this is a better option than choosing dry vans and temperature-controlled vans with monitoring capability for this case, it could be a sub-optimal choice for the retailers who may want to expand their businesses to a larger geographical territory in the long term, because it restricts the retailers from providing optimal quality fresh food to their customers located at greater distances, leading to a competitive disadvantage in the market.

On the other hand, the retailer may use the observations from this research to look at a hybrid choice of vans, with both dry vans and temperature-controlled vans. For example, when operating at distances $d_{ij} \leq d_{k_{2,3}}$, vans can be chosen such that part of the distance is served by dry vans and part of it is served by the second category of vans. This would help them in increasing their service region while simultaneously providing fresh food of optimal quality. It is also evident from the results obtained that the demand levels have no effect over the choice of vans. Fresh food wastage occurs regardless beyond a given threshold distance, and the condition is worse if it is not delivered with the appropriate choice of transport. These inferences are summarized in Table 11.

Table 11. A synthesis of trade-off of monitoring capability with distance and demand.

Distance	Low/High Demand
Short distance $d_{ij} \leq d_{k_1}$	Dry vans (non-temperature-controlled system without monitoring capability)
Medium travel distance $d_{ij} \in \left(d_{k_1}, d_{k_2}\right]$	Temperature-controlled vans without monitoring capability
Long travel distance $d_{ij} > d_{k2,3}$,	
$p > \left[\left(\left(\frac{1-r_{k_2}}{\Delta r_{23}}\right)\left(\Delta f_{23} + \Delta c_{23} d_{ij}\right)\right) - \left(f_{k_2} + c_{k_2} d_{ij}\right]\right.$	Temperature-controlled vans with monitoring capability
$p < \left[\left(\left(\frac{1-r_{k_2}}{\Delta r_{23}}\right)\left(\Delta f_{23} + \Delta c_{23} d_{ij}\right)\right) - \left(f_{k_2} + c_{k_2} d_{ij}\right]\right.$	Temperature-controlled vans without monitoring capability
$p = \left[\left(\left(\frac{1-r_{k_2}}{\Delta r_{23}}\right)\left(\Delta f_{23} + \Delta c_{23} d_{ij}\right)\right) - \left(f_{k_2} + c_{k_2} d_{ij}\right]\right.$	Either of the non-dry vans

This research is a part of a larger study of installing monitoring systems in the food supply chains of several companies across Europe, and some of the ideas in this model have been implemented during these activities. They helped us to gain a deeper understanding of the needs of logistical services depending on the nature of the project and expected quality. One of the retail stores, 'Cool-X', operating in the Netherlands, is making home deliveries after picking the products from retail stores. This company uses small cool packs to deliver cold and frozen items. These cool packs are filled with ice-cubes to maintain specific temperature ranges, such as from −5 °C to 2 °C. There are two different options possible: one is having the cool packs installed along with sensors and data connectivity, and the other option is having cool packs with only ice-cubes. The first option is used for long-distance travel or high-value products to avoid any quality loss, while option 2 is used for short-distance travel, thereby reaping the benefits of high-end technology monitoring for long range transport.

A case company Green-X, located in Luxemburg, is playing various roles in the food supply chain as suppliers, distributors, and retailers. When this company is working closely with the farmers, they prefer to use trucks or vans with no climate control options for food produce which can stay in normal temperature for a week, such as in the case of potatoes and carrots. However, the company is using temperature-controlled transport and warehouses for fresh vegetables and fruits with less than 5 days of shelf life. These trucks are fitted with sensors and connected to the cloud to monitor the temperature on the move. Mobile alert facilities are provided to some trucks which travel beyond a range of 50 miles. This is mainly to help the decision makers and to make sure that any remedial action should be possible immediately in case of abnormal temperature fluctuations.

More case studies documenting our experiences have been published [7,47,48]. Ref. [47] describe in detail the efforts made in implementing the control and monitoring system in vans of a last-mile delivery provider in The United Kingdom (UK). Ref. [7] describe the details of a similar system in a frozen food company, while [8] describe the experiences of transporting valuable human milk for a UK human milk bank. The motivations and barriers for companies for engaging in the control and monitoring system are discussed in [48], along with a discussion on business models. A detailed exploration of the costs, including environmental costs, has been carried out by [49] for selected case studies.

6. Conclusions

This paper addressed an important gap in the fresh food transportation literature by developing a novel prescriptive mathematical model to evaluate the cost-effective choice of transport in the presence of multiple van types to transport fresh food. For the purpose of this study, three types of vans, namely vans without temperature monitoring and control ability (dry vans), vans with temperature control without a monitoring facility, and vans with temperature control and monitoring capability, were considered. The proposed linear programming formulation integrates conventional transport network decisions, such as food quantity shipment and producer–retailer allocations, with van type choices to maintain food quality enroute. The model was solved using CPLEX and a Pyomo environment on two mixed instances initially, which contained all configurations of travel distances. By the method of inference, three theorems were proposed and proved to finally deduce the cost-effective choice of vans for cases of short-, medium-, and long-distance configurations. The findings from the three theorems were validated on several data sets comprising various combinations of travel distances, demand levels, and penalty costs, which also revealed that the optimal choice of vans is independent of demand levels under infinite vehicle resource availability. Importantly, the study derives a general expression of the trade-off point defined by the value of unit penalty cost, which makes the optimal choice of transport shift from vans without temperature monitoring capability to vans with temperature monitoring capability. Furthermore, sensitivity analysis was conducted to observe cost trade-offs and threshold penalties pertaining to the choice of vans for different types of perishables. These novel findings will be useful to food logistics operators to understand the economic implications of using dry or reefer vans for fresh food transportation.

The present work provides a strong foundation to investigate several other issues under additional complexities in the future for fresh food transport that, in other words, form the limitations of this study. For example, the model proposed in this work can be improved to evaluate optimal van choices under vehicle resource restrictions. Although the vehicle fleet composition can be derived easily for the current problem as they are treated as dependent decision variables, this can be further deeply examined by internalizing fleet composition as independent decision variables. More complicated vehicle routing models with different van types can be developed to explore complex trade-offs. It can also be further extended from a single type of food transport to multiple food types with different shelf lives. Newer vehicle routing models can be developed to identify the choice of these three types of vans after considering emissions from refrigeration. We could include the impact of variations in quality decay due to interaction between two or more fruits when carrying multiple perishable products. Furthermore, it was assumed here that all the vans are operating under a hire/lease model, whereas, in practice, large retailers may be interested to see cost–benefit trade-offs of investing on in-house transport resources. Finally, cost may not be the only factor influencing the choice of vans. In most cases, the appropriate choice of sensors is decided based on the specific application scenario and, therefore, could have other priorities affecting the choice of vans, such as the minimum accuracy and standards of sensors needed (for example if sensors with high levels of accuracy for relative humidity measurements are a necessary requirement), which can form interesting research avenues for future consideration and investigation.

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Appendix A

Table A1. Parameter notations for different types of vans.

Description	Notations		
	Dry Vans (k_1)	**Temperature-Controlled Vans without Monitoring Capability (k_2)**	**Temperature-Controlled Vans with Monitoring Capability (k_3)**
Fixed hiring cost per unit quantity	$f_{k_1} = f$	$f_{k_2} = f + \Delta f_{12}$	$f_{k_3} = f_{k_2} + \Delta f_{23}$
Variable transportation cost per unit quantity per unit distance	$c_{k_1} = c$	$c_{k_2} = c + \Delta c_{12}$	$c_{k_3} = c_{k_2} + \Delta c_{23}$

Table A1. *Cont.*

Description	Notations		
	Dry Vans (k_1)	**Temperature-Controlled Vans without Monitoring Capability (k_2)**	**Temperature-Controlled Vans with Monitoring Capability (k_3)**
Cost for fresh food loss per unit quantity	p	p	p
Distance limit (beyond this distance quality starts deteriorating)	$d_{k_1} = d_k$	$d_{k_2} = d_k + \Delta d_{k_{12}}$	$d_{k_3} = d_{k_2}$
Basic quantity loss factor	$r_{k_1} = r$	$r_{k_2} = r - \Delta r_{12}$	$r_{k_3} = r_{k_2} - \Delta r_{23}$

Appendix A.1. Proof of Theorem 1

All notations used for proving the theorems have been described in Table A1. For distances $d_{ij} \le d_{k_1}$,$z_{ijk_1} = 0$. As $d_k < d_k + \Delta d_{k_{12}}$ implies, $z_{ijk} = 0\ \forall k$. Hence, the cost for quality loss does not incur irrespective of the choice of vehicle. Considering the total cost of transportation through each type of vans without the cost for fresh food loss, we know that a quantity of $x = D$ (demand) must be transported. Total cost of transportation through dry vans, $TC^I_{k_1} = D(f + cd_{ij})$. Total cost of transportation through temperature-controlled vans without monitoring capability,$TC^I_{k_2} = D(f + \Delta f_{12} + cd_{ij} + \Delta c_{12} d_{ij}) = TC^I_{k_1} + D(\Delta f_{12} + \Delta c_{12} d_{ij})$. Total cost of transportation through temperature-controlled vans with monitoring capability, $TC^I_{k_3} = D(f + \Delta f_{12} + \Delta f_{23} + cd_{ij} + \Delta c_{12} d_{ij} + \Delta c_{23} d_{ij}) = TC^I_{k_1} + D(\Delta f_{12} + \Delta c_{12} d_{ij}) + D(\Delta f_{23} + \Delta c_{23} d_{ij}) = TC^I_{k_2} + D(\Delta f_{23} + \Delta c_{23} d_{ij})$. Now, $TC^I_{k_1} < TC^I_{k_1} + D(\Delta f + \Delta c_{12} d_{ij}) < TC^I_{k_2} + D(\Delta f_{23} + \Delta c_{23} d_{ij})$. Hence, $TC^I_{k_1} < TC^I_{k_2} < TC^I_{k_3}$, making dry vans the optimal choice for $d_{ij} \le d_{k_1}$.

Appendix A.2. Proof of Theorem 2

When distance $d_{ij} \in (d_{k_1}, d_{k_2})$,$d_{ij} > d_k$, therefore, $z_{ijk_1} = 1$. If dry vans are chosen, it would incur a cost of pxr_k for fresh food loss where the quantity of fresh food to be transported $x = \frac{D}{(1-r_{k_1})}$, while $z_{ijk_2} = z_{ijk_3} = 0$ since $d_{ij} < d_k + \Delta d_{k_{12}}$. Hence, for both temperature-controlled vans with and without monitoring capability there is no cost for quality loss. Considering the total cost for each type of van for this case:

Total cost of transportation through the dry van, $TC^{II}_{k_1} = \frac{D}{1-r}(f + cd_{ij} + pr) = \frac{1}{1-r}(TC^I_{k_1}) + \frac{prD}{1-r}$.

Total cost of transportation through temperature-controlled vans without monitoring capability, $TC^{II}_{k_2} = D(f + \Delta f_{12} + cd_{ij} + \Delta c_{12} d_{ij}) = TC^I_{k_1} + D(\Delta f_{12} + \Delta c_{12} d_{ij})$.

Total cost of transportation through temperature-controlled vans with monitoring capability, $TC^{II}_{k_3} = TC^I_{k_2} + D(\Delta f_{23} + \Delta c_{23} d_{ij})$.

From theorem 1 we know that $TC^I_{k_1} + D(\Delta f + \Delta c_{12} d_{ij}) < TC^I_{k_2} + D(\Delta f_{23} + \Delta c_{23} d_{ij})$. Hence, $TC^{II}_{k_2} < TC^{II}_{k_3}$. To check if $TC^{II}_{k_1} < TC^{II}_{k_2}$, it needs to be proved that $TC^{II}_{k_2} - TC^{II}_{k_1} > 0$.

$$TC^{II}_{k_2} - TC^{II}_{k_1} = \left(TC^I_{k_1} + D(\Delta f_{12} + \Delta c_{12} d_{ij})\right) - \left(\frac{1}{1-r}(TC^I_{k_1}) + \frac{prD}{1-r}\right) = TC^I_{k_1}\left(1 - \frac{1}{1-r}\right) + \left(TC^I_{k_2} - TC^I_{k_1}\right) - \left(\frac{prD}{1-r}\right)$$
$$= TC^I_{k_1}\left(\frac{-1}{1-r}\right) + TC^I_{k_2} - \frac{prD}{1-r} = TC^I_{k_2} - \left(TC^I_{k_1}\left(\frac{1}{1-r}\right) + \frac{prD}{1-r}\right)$$

We know that $TC^I_{k_1} < \frac{TC^I_{k_1}}{1-r}$ *also*, $TC^I_{k_2} < \left(\frac{1}{1-r}TC^I_{k_1} + \frac{prD}{1-r}\right)$, since the cost for quality loss is much higher. Therefore, $TC^{II}_{k_2} - TC^{II}_{k_1} > 0$. Hence, it is found that $TC^{II}_{k_1} < TC^{II}_{k_2}$, making it the optimal choice of van in this case.

Appendix A.3. Proof of Theorem 3

For distances $d_{ij} > d_{k_3}$,$z_{ijk_3} = 1$. As $d_k + \Delta d_{k_{12}} > d_k$ implies, $z_{ijk} = 1\ \forall k$. Therefore, in this case, irrespective of the choice of vehicle, all types of vans would incur costs due to fresh food loss. Considering the total cost of transportation for each type of van in this case:

Total cost of transportation through the dry van, $TC_{k_1}^{III} = \frac{D}{1-r}(f + cd_{ij} + pr) = \frac{1}{1-r}(TC_{k_1}^{I}) + \frac{prD}{1-r}$.

Total cost of transportation through temperature-controlled vans without monitoring capability, $TC_{k_2}^{III} = \frac{D}{1-\Delta r_{k_2}}(f_{k_2} + c_{k_2}d_{ij} + pr_{k_2})$.

Total cost of transportation through temperature-controlled vans with monitoring capability, $TC_{k_3}^{III} = \frac{D}{1-r_{k_2}+\Delta r_{23}}(f_{k_2} + \Delta f_{23} + c_{k_2}d_{ij} + \Delta c_{23}d_{ij} + pr_{k_2} - p\Delta r_{23})$.

Comparing $TC_{k_1}^{III}$ with $TC_{k_2}^{III}$, from theorem 1 we know that $TC_{k_1}^{I} < TC_{k_2}^{I}$. However, $\frac{1}{1-r} > \frac{1}{1-(r-\Delta r_{12})}$ and $\left(\frac{prD}{1-r+\Delta r_{12}} - \frac{p\Delta r_{12}D}{1-r+\Delta r_{12}}\right) < \frac{prD}{1-r}$. Thus, it can be inferred that $TC_{k_2}^{III} < TC_{k_1}^{III}$.

Now, subtracting $TC_{k_2}^{III}$ from $TC_{k_3}^{III}$, we obtain the following:

$$= D\left[\left(\frac{1}{1-r_{k_2}+\Delta r_{23}}(f_{k_2} + \Delta f_{23} + c_{k_2}d_{ij} + \Delta c_{23}d_{ij} + pr_{k_2} - p\Delta r_{23})\right) - \left(\frac{1}{1-\Delta r_{k_2}}(f_{k_2} + c_{k_2}d_{ij} + pr_{k_2})\right)\right]$$

$$= D\left[(f_{k_2} + c_{k_2}d_{ij} + pr_{k_2})\left(\frac{-\Delta r_{23}}{(1-r_{k_2}+\Delta r_{23})(1-\Delta r_{k_2})}\right) + \left(\frac{1}{1-r_{k_2}+\Delta r_{23}}(\Delta f_{23} + \Delta c_{23}d_{ij} - p\Delta r_{23})\right)\right]$$

To arrive at the threshold value of unit penalty cost for quality loss, let the above equation be below 0, as at this point temperature-controlled vans with monitoring capability would be the optimal choice of transport.

$$D\left[(f_{k_2} + c_{k_2}d_{ij} + pr_{k_2})\left(\frac{-\Delta r_{23}}{(1-r_{k_2}+\Delta r_{23})(1-\Delta r_{k_2})}\right) + \left(\frac{1}{1-r_{k_2}+\Delta r_{23}}(\Delta f_{23} + \Delta c_{23}d_{ij} - p\Delta r_{23})\right)\right] < 0$$

Rewriting the above equation:

$$\left[\frac{\Delta f_{23} + \Delta c_{23}d_{ij}}{1-r_{k_2}+\Delta r_{23}} - \frac{\Delta r_{23}(f_{k_2} + c_{k_2}d_{ij})}{(1-r_{k_2}+\Delta r_{23})(1-\Delta r_{k_2})}\right] < p\left[\frac{\Delta r_{23}}{(1-r_{k_2}+\Delta r_{23})} + \frac{\Delta r_{23}r_{k_2}}{(1-r_{k_2}+\Delta r_{23})(1-\Delta r_{k_2})}\right]$$

On simplifying, we arrive at the threshold unit penalty cost, $p > \left[\left(\left(\frac{1-r_k}{\Delta r_{23}}\right)(\Delta f_{23} + \Delta c_{23}d_{ij})\right) - (f_{k_2} + c_{k_2}d_{ij})\right]$. Hence, the unit penalty cost being more than this threshold penalty cost per unit would lead to the optimal choice of transport as temperature-controlled vans with monitoring capability.

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Review

Corporate Reporting on Food Waste by UK Seafood Companies: Literature Review and an Assessment of Current Practices

Mohammad Al-Tamimi, John De-Clerk Azure * and Ramakrishnan Ramanathan

Essex Business School, University of Essex, Essex CO4 3SQ, UK
* Correspondence: john.azure@essex.ac.uk

Abstract: Over 10% of the world's population is undernourished, yet 1/3 of all food produced each year is lost or wasted. Such a level of inefficiency in the global food system has a significant economic, social, and environmental impact which has elicited calls for urgent global action. This paper responds to this call by developing an interdisciplinary framework focusing on legal, regulatory, accounting, and reporting frameworks to improve the prevention or reduction of food loss and waste (FLW). Mobilising a literature review, this paper advances a three-pronged suggestion for tackling FLW in UK seafood companies: the development of technological solutions in the form of sensors; the enactment of a comprehensive legal and regulatory reporting template for seafood companies; and finally, the development of accounting standards that mandate reporting beyond the current Food and Waste Accounting and Reporting Standard by the Water Resources Institute (WRI), which is modelled on voluntary compliance.

Keywords: corporate reporting; interdisciplinary approach; food waste; UK seafood companies

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1. Introduction

While over 828 million people are underfed (over 10% of the world's population), one-third of all food produced is lost or squandered, worth around $1 trillion [1,2]. Food waste occurs during transportation from the food's point of production to its destination. In other words, some food ends up in waste bins of consumers and retailers or spoils due to poor transportation and harvesting practices. Food waste refers to all edible and non-edible materials discarded or diverted from the normal supply chain [3,4]. Such food is either unfit for consumption or is originally fit but intentionally discarded at the production, trade, or consumption phases, all of which are encompassed by food loss and waste (hereafter, FLW).

FLW is associated with ethical, financial, social, and environmental costs. Environmentally, for instance, it contributes 8% of greenhouse gas emissions (GHGE) [5]. To ensure and improve worldwide food security, reducing food waste has risen to the top of the political agenda worldwide [6,7]. The United Nations' Sustainable Development Goals (SDGs), approved in 2015, represent a landmark initiative to address some of the world's most critical and persistent issues. As part of the 2030 Agenda, 17 SDGs have been backed by 169 objectives and 232 indicators [8]. The issuance of SDG12.3, which targets the halving of food waste between 2007 and 2030, has accelerated efforts to reduce, prevent, and manage food waste. Despite such exertions and accomplishments, food waste is still a global issue [9]. Therefore, FLW needs to be further explored by governments and researchers to provide relevant parties with high-quality data to support decisions on how and where efforts and money (i.e., investment) should be applied. For example, research can improve methods of addressing FLW and its related difficulties, fostering innovation and new reduction ideas [10].

Corporate social and environmental disclosure is a reasonable societal commitment [11]. Reporting on food waste is necessary to track the progress toward reducing its impact on our lives. Despite the broad agreement by stakeholders concerning the adverse consequences and implications of FLW, there are challenges to firms' accounting and reporting on FLW. To effectively reduce FLW in the supply chain, businesses need accurate data on how much waste is produced and where it occurs. FLW accounting and reporting is a central element for policy design and interventions, given that what gets measured and reported on gets addressed.

Previous studies on food waste have focussed on the issue at the consumer level [12], organisational level, and supply chain level [13,14]. To date, no studies have focussed on reporting practices that facilitate more food waste reduction by wider aspects. This paper is the first of its kind to fill this important knowledge gap. The paper aims to discuss an interdisciplinary approach to tackling food waste, including the role of corporate reporting. In particular, we argue that the current FLW reporting status needs reform and profound consideration, especially regarding seafood waste. An interdisciplinary approach is essential because FLW reporting is complex and involves multiple stakeholders [6].

A sustainable food system is an evolving process in which attaining food and nutritional security should also support future generations' food and nutrition stability [15,16]. Access to food safety, quality, and environmental and social sustainability are all aspects of corporate social responsibility (CSR) [17]. This conceptual paper aims to identify and assess the relevant literature on food waste in the UK with more of a focus on seafood. This includes areas such as corporate reporting legislation and the use of technology.

This paper is structured as follows. After this introduction, a review of the literature on food waste in general and seafood waste in specific is presented. The consequences of food waste are discussed before reviewing national and international reduction efforts. Afterwards, reporting frameworks on accounting for food waste are discussed. Finally, a summary and recommendations are provided.

2. Literature Review

Over the last few decades, there has been a surge in awareness about the issue of food waste. Through extensive and regular statistics, several studies have demonstrated the magnitude of this problem [10]. As a result, many national and international organisations have prioritised the addressing of problems of food waste (by reduction, prevention, and management). Their efforts have frequently linked FLW to larger concerns about social justice, the environment, climate change, and managing scarce resources.

FLW studies have been carried out in developed countries such as the UK [18], the USA [19], Taiwan [20], and Italy [21]. Likewise, several studies have addressed food waste in developing countries such as South Africa [22], Brazil [23], Turkey [24], Malaysia [25], India, [26], Mexico [27], China [28], and Romania [29]. The literature shows relatively high differences between the countries regarding sources and typical food waste destinations. The techniques for handling FLW include destinations such as animal feeding, composting (or organic fertiliser), anaerobic digestion, incineration, and landfills (including illegal open dumping that is common in developing countries) [30,31].

Previous FLW studies have relied on different theories. One line of research used the theory of planned behaviour to examine household food waste behaviour change interventions e.g., [29,32–34]. On the other hand, Shove [35] provided a detailed critical appraisal of the social practice that broadens the view on food waste creation beyond individual psychological elements, including attitudes, behaviour, and choice. Regarding methodologies used, most previous studies have relied on quantitative methods to document FLW magnitude and solutions. On the other hand, several studies have relied on qualitative approaches, such as the case study approach (single or multiple), including Liljestrand [36], who applied semi-structured interviews and site visits to study logistics solutions for the reduction of FLW. Similarly, interviews were undertaken by Mena, Adenso-Diaz [37] in the UK and Spain, who found that tubers, vegetables, and fruit have the highest FLW levels.

2.1. Consequences of Food Waste

Previous studies have provided convincing evidence that FLW negatively affects the environment [38] and the economy, [39] while also posing moral dilemmas [40]. The environmental impact pertains to the produced emissions and the economic impact pertains to the costs of uneaten food. On the other hand, the moral or ethical issue is caused by the presence of people going hungry elsewhere.

Various governmental, private, and international programmes and researches have underlined the significance of FLW issues in recent years, including nutrition security, environmental effects, resource exploitation, and sustainable development [41]. If food is lost during production, then the land, water, energy, and inputs employed in its creation are wasted, and so is the resulting GHGE [1]. An estimated 40.7 million tonnes of food are wasted annually worldwide, which amounts to almost 26% of total food reserves, an amount of food for which there has not been found a use [42]. Cultivated but never consumed food uses an estimated 250 km^3 of fresh water annually and needs approximately 1.4 billion acres of land [43]. Several studies have focused on the wider impacts of seafood as a major type of food. For example, Liu, Lundqvist [28] have studied FLW in regards to its implications for a country's water and land resources.

Reducing food waste shrinks its significant effect on the environment, saves money [44], and makes companies look more morally sound and equitable [40]. Companies vary in their efforts and FLW reduction achievements. Per se, reduction appears to be an achievable and collaborative goal. However, there are many difficulties in corporate reporting, such as comparability, which mandatory standards of quantification and reporting can alleviate.

Those consequences may be avoided by reducing food waste since less food must be manufactured based on the agreed FWL hierarchies.

2.2. Food Waste in the UK: Facts and Reduction Efforts

Countries differ in the waste they generate. Waste generated in the UK is close to the global average but has a lower rate of food waste per capita than many developed and underdeveloped states [8], as shown in Figure 1 below.

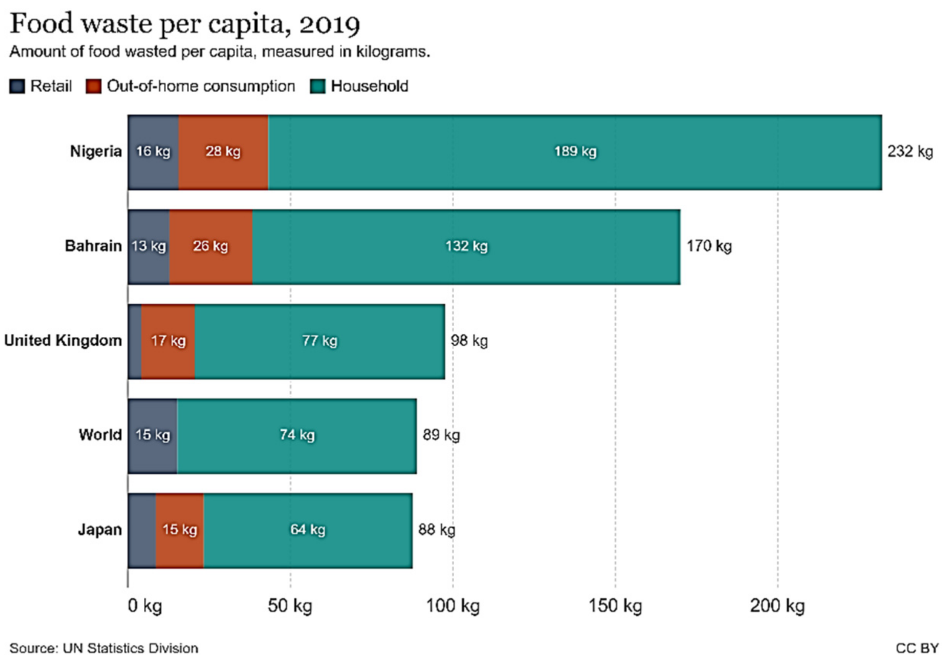

Figure 1. Food wasted per capita. Source: [45].

The figure shows that food wasted in kilograms per capita differs significantly among countries (developing and developed). Figure 2 below presents the total annual household food waste produced in selected countries in 2021.

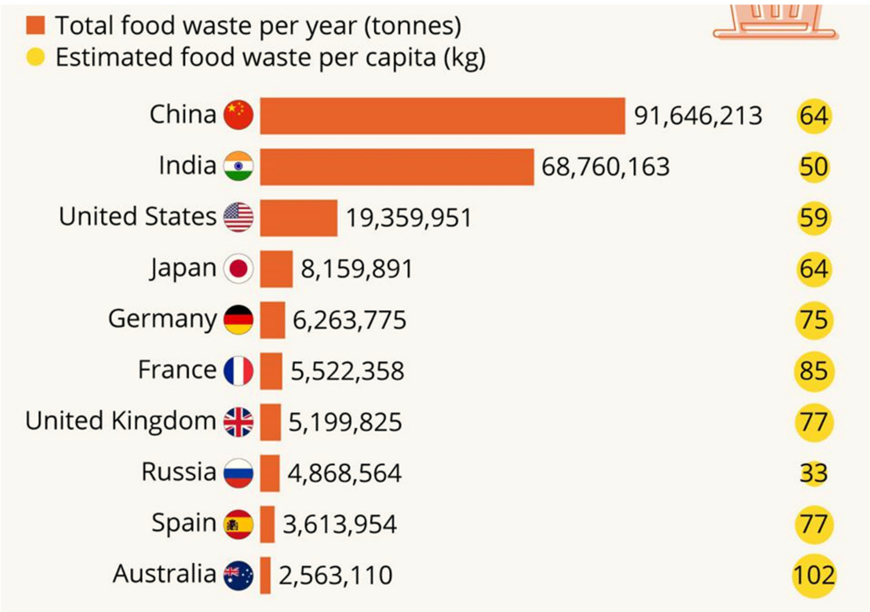

Figure 2. Total and per capita food waste in selected countries. Source: Statista, 2022.

The reasons behind food waste vary from cultural, political, economic, and geographical factors, as have been compiled in some literature review papers e.g., [46]. The data about the causes of food waste and the impediments to its reduction remain complex and dispersed [47]. Consequently, some studies have suggested complex techniques to address food waste, such as the food-waste management decision tree [48]. Discussing these techniques is beyond the current study objectives.

Governmental interventions have centred on preventing waste from entering landfills using legislation, taxes, and public awareness [37]. Some of the largest grocery chains in the UK have adopted corporate policies that stress the need to reduce food waste [49]. Despite following SDG 12.3, there is no mandatory food waste reporting yet in the UK, but consultations (by seeking views and evidence on the type of business scope, material scope, reporting processes and compliance and enforcement [46,50]) are ongoing to view opinions on reporting by large UK food firms [50]. The UK government has been seeking to guarantee an adequate decrease in food waste to sustain development and reap the advantages, especially because, owing to a lack of awareness, motivation, and confidence in their abilities to do so, major food enterprises do not track and report food waste [50]. A food business includes firms working in packing, manufacturing, and wholesaling, as well as retailers, caterers, and food services (e.g., restaurants).

The UK's suggested reporting model uses reliable templates such as the Waste and Resources Action Programme (WRAP). Larger firms must report the data to the regulator (the Environment Agency). In addition, WRAP works with United Against Food Waste Netherlands to coordinate efforts on food waste from retailers, collaborate on FLW technologies, and require supplier reporting [51]. For instance, 27 of Tesco's own-brand suppliers (around 50% of its fresh food sales) have released statistics on their food waste for the second year in a row. These initiatives can be used as case studies to encourage other retailers toward more transparency.

Due to inefficient food transportation and consumption, high-income nations have a larger per capita food waste impact on the environment than low-income countries [43]. However, following a state-wide programme organised by the government, retailers, and WRAP, the UK reduced food waste in homes by an impressive 21 per cent between 2007 and 2012 [52]. For over a decade, WRAP has tracked and published data on FLW in the UK, and household food and drink waste figures were first released by WRAP in 2008 (WRAP, 2011). It is argued that the UK is the only nation on pace to meet the UN's 2030 goals, with a 27% decrease in FLW between 2007 to 2018 [53]. The UK government aims to improve future generations' environmental conditions and reduce food supply chain emissions and waste ('A Green Future: Our 25-Year Plan to Improve the Environment' sets out what the government will do to improve the environment within a generation. This report is available on: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/693158/25-year-environment-plan.pdf, accessed on 25 November 2022). In particular, the goal is to reduce the GHGE intensity of food and drink eaten in the UK by one-fifth by 2025 and reduce per capita UK food waste. By promoting better and more environmentally friendly eating and drinking habits, the UK will be well on its way to achieving SDG 12.3.

The Courtauld Commitment is a series of commitments started in 2005, and in co-operation with WRAP and large firms, that aim to explore solutions throughout the full supply chain to minimise domestic packaging and food waste. Since its first version, it has proved to be a durable and effective agent of change and has decreased the carbon footprint and broader environmental effect of the UK's food and beverage industry. Courtauld Commitment 2025 is a bold voluntary agreement engaging organisations throughout the food supply chain. The pledge looks across supply chains to discover efficiencies such as educating customers. The realised savings will be evaluated using standard metrics aligned with international best practices.

The amount of food waste that can be saved is high; nearly 75% of the 6.6 million tonnes of household food waste discarded in the UK each year is food that could have been consumed. Therefore, FLW reduction plans and efforts need to be reviewed continuously to ensure that country-level targets that participate toward the global targets can be met.

2.3. Seafood Waste: Nature and Uniqueness

Seafood is an important type of food [54] that makes up a significant percentage of food consumed by many nations. Nearly three billion people worldwide depend on wild-caught and farmed seafood as a principal source of animal protein (20% in 2013), making it a vital dietary source [9]. Approximately twice as much seafood is consumed worldwide as in the last 50 years with the growth of the world's population [55]. Seafood is a commodity group that includes "freshwater fish, demersal fish, pelagic fish, other marine fish, crustaceans, other mollusk, cephalopods, other aquatic products, aquatic mammal meat, other aquatic animals, aquatic plants" p. 10 [2].

Seafood has already been subject to many problems, such as overfishing, pollution, and the global warming catastrophe that seriously endangers fish stocks. Because fish consumption is expected to double by 2050, international authorities (e.g., FAO) are becoming more concerned about seafood waste, arguing that everyone around the globe has to take action. Researchers need to know where most food waste happens in the first place. The nations with the largest catch fisheries generate the most waste, including the USA, Canada, Norway, Spain, Korea, China, and India [56]; thus, many studies have focused on certain locations when addressing seafood waste [5,15,57–61]. Therefore, the significance of the UK context requires more research.

Thirty-five percent of fish and seafood is wasted annually [5]. A significant difficulty in managing natural resources, particularly fisheries, is striking the right balance between the competing needs of national and global economic growth and long-term species viability and ecosystem sustainability [62]. As a result of overfishing and fishing practices that harm marine ecosystems, fish stocks worldwide have been under growing strain. Pete Pearson, head of food waste at The World Wide Fund for Nature (WWF), explains that, since fish are wild creatures, we exploit nature when we throw them away [63].

Seafood differs from other food types in terms of its nature, usage, and wastage. Due to their perishability and fragility, fish are particularly susceptible to high spoilage and loss throughout the supply chain. The wastage of seafood is high because it needs intensive supply chain management at every step (e.g., high hygiene levels and specific temperature conditions to remain edible and fresh).

Seafood waste comes from different sources, such as the traditional fishery by-products of fish meal, fish body, and liver oils, fish maw, isinglass, etc. Some other by-products generally processed from fish and fish waste include fish protein concentrate, glue, gelatine, pearl essence, peptones, amino acids, protamine, and fish skin leather. These make seafood waste measurements complex and hard to generally agree upon; thus, direct comparisons between recorded or estimated quantities of waste are challenging. Around 1.5 million tonnes of waste crab, shrimp, and lobster shells are generated annually in southeast Asia alone, accounting for about 6–8 million tonnes of waste worldwide [64].

In the UK, processed fish have a significant amount of inedible material, ranging from 58% for white fish such as cod to 88% for shellfish such as scallops [65]. The high levels of inevitable by-products and the extremely variable characteristics of fish processing procedures mean it is difficult to calculate the amount of waste that might have been avoided. Reductions in seafood waste were expected to improve after WRAP. However, before 2007, sustainable fishing practices were difficult to identify [66]. Moreover, because impacts on producers and the implementation of sustainable fishing practices are currently unidentifiable, it is difficult to tell whether the industry is improving. A review by Hasan, Hecht [67] has highlighted the absence of government statistics on the percentage of aquaculture production in developing nations that utilise aquafeeds (industrial and farm-made) or complete food products (such as junk fish) by primary cultivated species group or farming technique.

The UK has been funding a non-ministerial public agency known as the 'Sea Fish Industry Authority' (Seafish), founded in 1981, to support the fish sector's efforts to promote high-quality, environmentally friendly seafood. Seafish recommends that seafood manufacturers consider where and how waste is generated during processing and across the larger supply chain. In addition, Seafish has organised creative campaigns to emphasise the significance of the shift to a circular economy. For instance, it launched the nationwide initiative of 'Zero Waste Week' where participants include householders, businesses, schools, and community groups who can inspire more people to recycle and decrease the amount of waste sent to landfills (i.e., consider how we spend our limited resources) . Thus, corporate reporting should focus on both reduction quantities (tonnes and percentages) and destinations. Ultimately, to improve resource efficiency, companies should be able to accurately measure such waste. The innovative and convectional uses of seafood waste have been addressed by many scholars e.g., [68,69].

In summary, to aid in designing food waste prevention strategies, it is essential to plot elements of waste generation to expand our understanding of the levels of manufacturing, retail and household seafood waste [47].

2.4. Discussion of Literature Review

The relevant literature to the following three aspect is discussed below.

2.4.1. Technology Role in FLW

Although one-third of UK consumers throw away food due to its use-by date, sixty per cent of the food we throw away yearly is safe to consume. Technological advancement may help reduce the waste that is believed to be inedible regardless of its shape. For example, rather than wasting food by adhering to 'use-by' dates, we can use sensors to measure how fresh the food is.

Since seafood requires a complex storage environment, it is argued that sensors can be useful for reducing seafood waste during the manufacturing and retailing process. Experts have developed sensors, in laboratories, to help overcome food waste since they are far more sensitive. They can help people to understand when to eat the food or not, reducing food waste. Lab-made sensors can be significantly more sensitive than a human nose and can signal not just when food has exceeded a particular level of spoilage (needs to be thrown out) but also when food is almost bad and needs to be eaten or redistributed before being wasted.

Technological advancements can help reduce food waste at various stages in the supply chain. Previous studies (e.g., [70]) have demonstrated that companies' investments in such technologies are justifiable given the cost savings. Investments in technology can be included in companies' annual reports as part of their efforts in food waste reduction

2.4.2. Role of Legislation, Customers' Rights, and Labelling

In addition to voluntary reduction practices by companies, legal compliance is believed to allow a more systematic reduction in seafood waste. Yet, legislation around seafood waste is limited despite its huge impact on the environment and economy. The United Nations and the European Union are two world system organisations tasked with implementing various legislative measures to attain this kind of balance on a global and regional scale, as well as fostering collaboration among its member governments [62]. Three aspects are relevant to legislations around food waste: GHGE, packaging and disposal (destination).

A serious impact of food waste is gas emissions; if FLW is reduced, more emissions can be avoided. Accordingly, legal requirements need to be strengthened, especially to alleviate the impact of waste on the environment. Moreover, both reporting and audits are important in achieving global food waste reduction targets. Therefore, companies would be held accountable through public reporting and more motivated by voluntary reporting. Many UK retailers, such as Tesco, are pioneers in food waste reduction by leading the charge concerning food waste reporting and auditing.

Legislation can also be revised to support innovative uses of seafood waste. This sector discards about 10,000 tonnes of shellfish annually. Thus, the processing business must find ways to increase the marketability and shelf life of freshly caught or farmed fish. Plastics have long been the primary solution for the shelf-life problem. Furthermore, Chitin, abundant in discarded shellfish such as crab shells and squid feathers, can be used to create valuable packing substances [69,71]. Therefore, more regulations are deemed necessary to reduce FLW and plastic use simultaneously.

Another relevant aspect is labelling. Governments are involved in reducing food waste and protecting consumers' rights since both are related. In other words, sometimes food is wasted to comply with health and consumer safety laws. For instance, removing contaminated meat from shelves wastes resources but protects human health. This makes food waste reduction a more complicated task. Therefore, companies need to pay more attention to issues related to safe usages, such as clear 'use by' directions and legible labelling. The UK laws specify the 'use by' rules that leads foods to become former foodstuffs (The UK's regulations state that: "Foods of animal origin or foods that contain products of animal origin and are intended for human consumption may be removed from sale when they: have passed their sell by or use by date". Regulations are available at https://www.gov.uk/guidance/how-food-businesses-must-dispose-of-food-and-former-foodstuffs, accessed on 19 August 2022).

The nature of seafood makes it very different from other food in terms of labelling rules. For example, while seafood has labels for 'use by' to highlight the possible risks to safety, fruit, on the other hand, has 'best before' labels. As a result, improved labelling rules can help reduce food waste. However, different food types necessitate different rules and guidelines. For instance, it has been announced that M&S would be removing 'best before' labels from 300 fruit and vegetable items to cut food waste, instead allowing customers to use their judgment regarding food suitability for eating (from the Guardian, available online: https://www.theguardian.com/environment/2022/jul/17/ms-to-remove-best-before-labels-from-300-fruit-and-veg-items-to-cut-food-waste, accessed on 19 August 2022). Reducing seafood waste requires balancing consumers' rights and protecting the environment.

2.4.3. Reporting Frameworks on Accounting for Food Waste

In general, lost and wasted food is denoted by the difference between the food supply and the food consumed by the population [19]. Countries are believed to differ (e.g., wealthy vs. unwealthy) in the proportion of food wasted to the overall food produced. However, waste data may not be easily comparable between countries/companies due to differences in how they classify and record waste. Therefore, global FLW standards are essential in order to increase comparability and thus facilitate the best reduction results. Consequently, this may necessitate more national laws and regulations to optimally reduce FLW. Consequently, corporations, governments, and other groups have introduced some worldwide frameworks to aid in the monitoring, reporting, and managing of FLW.

The Waste and Resources Action Programme (WRAP), a British registered charity established in 2000, seeks to reduce food, packaging, and supply chain waste globally and improve its sustainability. It aims at lowering GHE, preserving natural resources, and assisting people in saving money by altering how food is produced and consumed. Collaboration, investigation, and bravery are necessary for transformations of this magnitude. All will have a greater effect on people and the environment [72]. WRAP is meant to aid organisations, communities, and individuals in their efforts to recycle, reuse, and cut down on food waste (e.g., 'Love Food, Hate Waste' and 'Recycle Now' campaigns). The scope of WRAP's operations has been expanding globally through collaboration with UNEP and the FAO and the creation of a global food waste guidelines tool [73]. Worldwide, food and beverage voluntary agreements have benefited from WRAP's assistance [74]. WRAP experts have created joint initiatives that help businesses cut down on food waste and GHGE while safeguarding vital water supplies. As of 2022, 351 UK organisations are committed to WRAP, many of which are seafood companies [75].

Food waste in the UK, based on a (2018) report by WRAP, includes 6.6 million tonnes (70%) from households, 1.5 million tonnes (16%) from manufacturers, 1.1 million tonnes (12%) from hospitality and food service and 0.3 million tonnes (3%) from the retail industry [53]. When food items are abandoned or diverted from the supply chain, they are termed 'food waste' and include either edible or non-edible parts [3,4]. The ethical point of view considers that major retailers should address the issue with their suppliers, which may conflict with their profit maximisation interests. A company's balance between generating a profit and doing good for the community is the essence of corporate social responsibility. In essence, the Seafish charity and the broader seafood business highly value social responsibility.

WRAP studies show that five stores had disclosed time-series data on FLW from their operations, four of which indicates a decrease from 2013 to 2017/18 [53]. Efforts to reduce food waste may be made at every stage of the supply chain and what is done (or not done) in one section of the chain impacts others. Therefore, actions should not be limited to targeting individual parties in the chain [64]. Reporting requirements should consider seafood supply chain complexities by disclosing the cooperation between all actors and parties [6].

The legislative opportunity to effectively reduce FLW is essential for the UK because it emphasises businesses' duties concerning waste management and use. Specifically, business undertakings have to take all possible measures to follow the FLW hierarchy as follows: (a) prevention; (b) preparing for re-use; (c) recycling; (d) other recovery (for example energy recovery); and lastly (e) disposal to landfill [76].

2.5. Recommendations for Regulatory Reform

It is generally agreed that reporting is a source of corporate accountability [66]. Drawing on stakeholder theory, all people, organisations, and governments are interested and should actively participate in FLW reduction plans. This requires compliance with FLW and emissions regulations, followed by reporting. FLW reporting is still voluntary in the UK and whether non-financial information should be voluntary or compulsory in corporate reports is a contentious issue. Consultations by the UK government aim to obtain opinions on whether to mandate FLW reporting or keep everything as it is.

Based on the relevant literature and the breadth of the seafood FLW issues, this paper suggests three action points that can form an interdisciplinary framework to help tackle food waste in the UK as follows.

- Technological advancements can help reduce food waste at various stages in the supply chain. For example, sensors developed by scientists offer cause for optimism in addressing seafood waste and loss during the manufacturing stage.
- Legislation can be reviewed and transformed to include more legal requirements, especially on the impact of waste on the environment. For instance, food waste reduction destinations need to be considered in terms of minimizing emissions . Thus, it is expected that legal compliance, in addition to voluntary initiatives by companies, will lead to a further decrease in seafood waste.
- Corporate reporting rules can be enforced to keep firms more transparent about their reduction strategies and their performances toward the achievement of their food waste reduction targets. Pioneering FLW reduction companies such as Tesco argue that, unless obligatory reporting is implemented, the UK will fall short of the SDG on food waste. Therefore, the UK government's consultation seeking views on mandatory reporting is essential. However, the government is still unclear as to whether the tendency toward more rules in this matter will continue or not. Nevertheless, WRAP has an optimistic view and argues that if present trends continue, the UK is on track to achieve UN SDG 12.3 [53].

The paucity of information on the progress toward decreasing food waste hinders the achievement of the SDG 12.3 target [52]. Given the weak compliance with the current voluntary framework, a shift must be made toward mandatory sources of information. In general, for the aspects of FLW that are improving, mandatory regulations should be increased (such as GHGE).

The ambitious commitments of retailers involve other aspects, such as packaging, that aim at saving the environment. In several food industries, reducing food waste may help reduce related packaging waste and vice versa. Therefore, mandating regulations on packaging (e.g., reducing packaging waste) may increase material efficiency and minimise the cost of waste management. Food packaging has attracted researchers' attention since it is associated with more waste. There are opportunities for firms to reduce certain kinds of packaging, such as plastic, to avoid the plastic packaging tax. Those relevant to seafood are available on the Seafish website.

More research is required to examine possible barriers that may prevent companies from measuring and reporting food waste, such as a lack of knowledge regarding FLW, motivation, and confidence in businesses' skills to measure it robustly. Therefore, stronger business collaboration toward global targets may be ensured if measurement training and reporting were mandatory.

Figure 3 presents the proposed framework to foster FLW reduction in the UK.

2.6. The Role of FLW Reporting

All phases of the supply chain (from collection through distribution to final consumers) must be included in any comprehensive strategy towards reducing FLW. As a technique to promote the expansion of environmental reporting, it has been proposed by Harte and Owen [77] that compliance with external standards be explored. This is because a company not only learns the extent to which its activities contribute to food waste but also gains a clearer picture of the sources of that waste and the damage it causes. This helps in overcoming any lack of data and paving the way for more focused strategies to cut down on food waste. Effective policies for FLW reduction are based on measuring and tracking wastage. Accordingly, accurate and reliable corporate reporting is essential in monitoring businesses' performance toward global and national targets. However, in the UK, FLW reporting is still not mandatory.

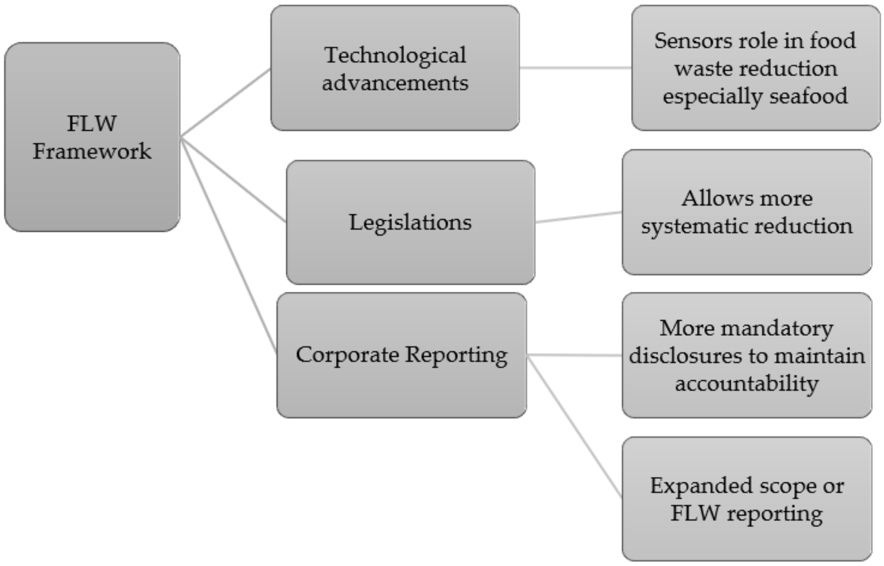

Figure 3. Multidisciplinary framework to address seafood waste in the UK.

Out of the UK's ten targets at business, industry, or national levels, only three include mandatory reporting (human rights, plastics, and climate change). In fact, the UK's strategy to reduce FLW in the business sector has been entirely voluntary, with action conducted via agreements similar to the Courtauld Commitment 1 (introduced in 2005), the latest version of which was, in 2021, introduced for Commitment by 2030. In addition, the Food Foundation has launched 'The Plating Up Progress' project, a set of measures covering ten different categories to evaluate companies' overall progress towards more healthy, equitable, and environmentally friendly food systems. These indicators are meant to promote systems thinking and more openness for enterprises. Moreover, stakeholders' (such as investors) engagement in these problems may be boosted by those with authority throughout the organisation's future activity.

The UK government has urged firms to actively participate in WRAP's framework . Larger food enterprises have also been encouraged to establish waste food minimisation objectives per SDG 12.3 and report on those. In addition, the UK plans to collect data on various national FLW indicators to gauge the efficacy of its Resources and Waste Strategy (RWS). RWS integrates immediate measures with long-term promises, providing a clear policy trajectory in keeping with the 25-Year Environment Plan [53].

Currently, around 200 large food companies already measure their food waste as part of WRAP and have attained financial and environmental advantages [53]. For example, 26 prominent UK-based businesses (comprising shops, caterers, quick service, and casual dining restaurants), evaluated in 2020 by the 'Plating Up Progress', revealed that commitments and disclosures on operational food waste reduction, in general, are stronger than those targeting supply chain food waste. Therefore, FLW reduction may be improved if specialised standards are applied for diverse supply chain participants, such as restaurants.

Seafood is the planet's most widely traded food product (Koonse, 2016), which makes its supply chain complex and prone to many issues, such as mislabeling (Shehata et al., 2019). Such issues can make the efforts of waste reduction harder. A satisfactory level of reporting by seafood firms is made more challenging due to its complexity. Supporting domestic seafood production, year-round employment, the recovery of endangered species and their habitats, and fortifying coastal ecosystems depend on marine aquaculture (often called farmed seafood) [65].

Concerning fishermen, the FAO has highlighted that, when state entities report best practices that are clear and effective, such as control measures for fish harvesting, there is a reduction in bycatch and associated mortality [78]. Such disclosure guidelines help make firms more accountable. Non-financial and website disclosures can signify CSR as a strategic objective of firms [79].

In summary, data availability and reporting are vital to track progress, but corporate reporting also relies on good data. The Food Foundation (2022) argues that good FLW data are essential for three parties; for businesses to drive improvements in their operations and supply chains, for investors to comprehend risks and prospects of investment, and for governments to evaluate progress towards nationwide targets. Improved FLW reporting needs to focus more on the aspects of the role of the consumers, of supply chain participants, and GHGE.

2.6.1. Cooperation with Consumers

Food's ultimate destination is to be eaten by consumers. While attitudes regarding food waste have changed, most people in the UK still believe that they do not produce any food waste. This is because they misunderstand the broader concept of waste. Governments worldwide have continuously encouraged consumers to reduce food waste. However, government cooperation with customers may not be sufficient to achieve the reduction targets effectively. Therefore, retailers can improve the role of the consumer since food waste is fairly measurable (i.e., quantities are recorded).

Moreover, regulators can emphasise the importance of consumer education. For instance, food safety and storage basics, as well as composting basics, can be learned by consumers so they can actively participate in food waste reduction. According to Abeliotis, Lasaridi [80], the skills and knowledge subcategory of food waste preventative strategies include common-sense consumer practices such as making lists and scheduling meals in advance. Businesses need to be more transparent in reporting on their efforts in this matter.

The focus on consumers is necessary for the UK case because, in wealthy nations, food waste occurs most often during consumption [1,81]. Consumers can be educated on the following points. First, FLW reduction has a business case; the typical UK home may save £500 annually [73]. Second, studying consumers' needs and preferences is essential since FLW reduction could be enhanced by matching the demand and supply of food. Overproduction and over-display lead to more waste [82]; thus, food crises may occur due to a disconnect between supply and demand and poor internal or external communication. Third, successful initiatives to reduce food waste must determine 'why' people throw perfectly good food away. Therefore, many retailers have removed 'best before' dates for fruit and vegetables. Fourth, consumption strategies, such as consumer campaigns and Marine Stewardship Council certification, have greatly progressed [66]. Still, greater attention must be paid to the intersection between production and consumption. Finally, companies may cooperate with consumers by effectively stressing the value of FLW reduction and connecting this to the lowering of GHGE, among other important social and economic advantages (e.g., increased food prices for consumers and businesses if FLW is not reduced). The role of consumers needs to be strengthened since their involvement in reducing GHGE is crucial (by reducing avoidable waste).

2.6.2. Supply Chain Participants

Food is wasted in multiple locations and involves different supply chain participants. For example, research undertaken by WRAP found that the UK wasted 6.6 million tonnes of household food in 2018 [53]. The literature on seafood waste reduction has focused on techniques and the 'know-how' category that covers prevention methods, since these are preferable in the food waste hierarchy. These range from focusing on households to focusing on retailers and businesses. Several studies have discussed consumer behaviours, such as using shopping lists and meal plans, while others have focused on conceptual frameworks to address how some businesses address food waste (e.g., those in the hospitality industry) [83]. WRAP argues that firms must exert more effort to curb pollution (i.e., emissions) and provides helpful resources for food and beverage companies looking to minimise their own Scope 1 and 2 GHGE from internal operations.

Moreover, prior research shows that food waste might be connected to the increased power of some supply chain participants. As a result of their tremendous market dominance in Australia, supermarkets unfairly claim CSR credit for cutting down on food waste, even as other players in the supply chain shoulder the monetary and ethical costs of this practice [41] (Australia, Japan, Austria, Belgium, Denmark, Kenya, and NZ require retailers to report food waste [51]). Accordingly, supermarkets can be primary adopters of mandated food waste reporting.

2.6.3. Reporting on Greenhouse Gas Emissions

FLW has increased importance due to its contribution to GHG emissions. Emissions from wasted food increase global warming, to an extent that approaches that of the world's automobiles (around 87%). If it were a nation, FLW would be the third-largest contributor to global warming [84]. The food industry is responsible for around 30% of global energy usage p. 3 [1], and around 22% of total emissions. Food processing emits 6%, retail and distribution emits 7%, food consumption emits 8%, and food disposal emits 6% [38].

In the UK, the role of FLW corporate reporting in climate change is partially/indirectly required since quoted companies and certain larger companies are required to report on their Scope 1 and Scope 2 GHGE. Scope 3 reporting is encouraged but remains voluntary (Source: UK government website. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/850130/Env-reporting-guidance_inc_SECR_31March.pdf, accessed on 23 November 2022). The UK government has solicited feedback on a proposal to mandate FLW reporting to protect the environment. Yet, there is a lack of compliance on the part of firms in disclosing emissions caused by or related to food waste. The progress of businesses in reporting GHGE is considerable in certain areas but slower in others. The most highly scored metrics in the UK include Scope 1 and 2 GHGE and 'operational' food waste reduction (Scope 1: All direct emissions from company vehicles and facilities. Scope 2: Indirect emissions from electricity used or purchased by the company. Scope 3: All other upstream and downstream emissions in the value chain, such as those related to procurement, waste, water and travel.). Annual reductions in food waste that have been quantified using this approach can also be used to demonstrate reductions in Scope 3, which covers emissions caused by waste disposal. It has been argued that implementing compulsory food waste reporting in the UK would assist in achieving the goals of the Courtauld Commitment 2025 and the WRAP roadmap. WRAP has developed the first ever technique for reliably measuring and reporting GHGE from the production and consumption of food and drink. Given the lack of voluntary disclosure, we can argue for an increase in mandatory reporting on food waste to maintain GHGE reduction performance and to strengthen the existing mandatory reporting requirements on GHGE.

In summary, firms' current initiatives and reporting compliance with developed frameworks can make them more accountable regarding their environmental impact. Accordingly, holding seafood producers accountable for FLW impact is possible by adopting a production chain perspective, making manufacturers more transparent, and imposing production chain guidelines [66].

3. Conclusions and Recommendations

Cooperation and effort coordination between companies, policymakers, and stakeholders are necessary to achieve FLW reduction targets. FLW reduction help save the environment and scarce resources and saves money. The FLW reduction business case is proven for governments, businesses, and individuals. However, action is required to maintain progress toward global reduction targets. This project suggests three aspects that can form an interdisciplinary framework to help tackle food waste in the UK. First, technological advancements such as sensors can help reduce food waste at various stages in the seafood supply chain. Prior studies, e.g., [70], have shown the business case for FLW, justifying companies' investment in such technologies. Second, legislation can be reviewed and transformed to include more legal requirements, especially on the impact of waste on the environment, since more food waste means more emissions that can be avoided. Therefore, in addition to the voluntary actions by companies, legal compliance is believed to allow more reduction in seafood waste. Third, financial reporting guidelines such as The Food Loss and Waste Accounting and Reporting Standard developed in 2016 by the Water Resources Institute (WRI) can be enforced to promote international consistency, comprehensiveness, and transparency in FLW reporting by entities beyond the current voluntary approach to reporting. As Peter Drucker argued decades ago, what gets measured gets done. Enforced reporting and measurement standards and governmental regulations could significantly improve FLW reduction.

Beyond governmental regulations and accounting and reporting standards for quantifying and reporting FLW, ongoing scientific research is critical in developing further understanding and building a concerted global action toward its reduction. Prior research has highlighted the significant economic, social, and environmental impact of FLW, which is beginning to garner the attention of researchers. As a result, companies and governments have committed to global FLW reduction targets. However, previous studies have revealed inconsistent compliance with food waste reporting guidelines by firms committed to WRAP.

Several issues relevant to corporate reporting are important to underline based on this literature review. First, several firms have proclaimed their intention to reduce food waste; however, evaluating their progress without relevant evidence is difficult. Mandatory, comparable and consistent rules are best at providing such evidence. Therefore, despite WRAP's optimism regarding the possibility of achieving SDG 12.3, this paper supports mandating food waste reporting requirements. Second, there is a noticeable lack of research on FLW creative initiatives and solutions (e.g., destination) and thus reporting items other than the frameworks which can be beneficial. New waste reduction techniques and destinations are parts of initiatives reported by few studies. Third, a high percentage of seafood waste is caused by the manufacturing process, which means that technology can be applied to reduce such waste.

Overall, governments and corporations worldwide are taking action to reduce FLW. Nevertheless, there is a need for enhanced knowledge of how much food is lost or wasted inside a country's borders, or as a result of its activities, and supply networks. In addition, the lack of a universally accepted definition of FLW and a standardised accounting and reporting structure makes it difficult to compare data and formulate effective solutions. Accordingly, more national and international regulations, including corporate reporting, are required in order to achieve SDG targets. The following points are essential. First, measuring and reporting FLW delivers indirect advantages by assisting enterprises' food waste reductions, as outlined in the Waste (England and Wales) Regulations 2011. Second, breaking down the sources of waste is crucial to develop better applicable standards consistent with the FLW hierarchy and GHGE reduction targets. Lastly, case studies and best reporting practices (e.g., based on the WRAP framework) must be regularly publicised to inspire other businesses.

Lastly, the limitation of this review paper is its lack of full analysis of prior literature. Therefore, we recommend that future research conduct wider scope reviews to suggest more compressive approaches toward reducing FLW.

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Motivations and Challenges for Food Companies in Using IoT Sensors for Reducing Food Waste: Some Insights and a Road Map for the Future

Ramakrishnan Ramanathan [1,*], Yanqing Duan [2], Tahmina Ajmal [3], Katarzyna Pelc [2], James Gillespie [4], Sahar Ahmadzadeh [2], Joan Condell [4], Imke Hermens [5] and Usha Ramanathan [6]

1 Essex Business School, University of Essex–Southend Campus, Elmer Approach, Southend-on-Sea, Essex SS1 1LW, UK
2 Business and Management Research Institute (BMRI), University of Bedfordshire, Park Square, Luton LU1 3JU, UK
3 Research Institute of Smart Cities, University of Bedfordshire, Park Square, Luton LU1 3JU, UK
4 Computer Science Research Institute (CSRI), School of Computing, Engineering and Intelligent Systems (SCEIS), Ulster University, Northland Road, L'Derry BT48 7JL, UK
5 Whysor B.V., Brandemolen 65, 5944 ND Arcen, The Netherlands
6 Nottingham Business School, Nottingham Trent University, Nottingham NG1 4FQ, UK
* Correspondence: r.ramanathan@essex.ac.uk

Abstract: Food waste is a serious problem worldwide, including in Europe. Research efforts are being carried out to reduce food waste. In this paper, we focus on using modern digital technologies (also known as Industry 4.0 technologies) to reduce waste in food supply chains. Based on interactions with a number of food companies in Europe over the last four years using Action Research, we provide new insights on the motivations and challenges for food companies when they are engaged in the use of technologies for reducing food waste in their supply chains. Motivations for firms include improved food quality of their produce, improved reliability, support in meeting legal requirements, a green image, and improved revenues from selling the food that has been saved. However, data security issues and trust issues posed challenges in using these technologies. Since this is an emerging area of research, we look at potential business models for technology companies for working with food companies in reducing food waste, identify value propositions and value capture, and look at how these investments in technologies can improve the sustainability of food businesses. We believe technology companies can leverage the opportunities, develop new business models with value propositions around the use of technologies, and support food companies via timely alerts in case of potential quality issues. Value capture occurs via the sale of hardware and subscriptions.

Keywords: food waste; Industry 4.0; business models; motivations; challenges

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1. Introduction to Food Waste

The food sector accounts for 22 percent of global GHG emissions. The importance of reducing food waste has been well recognized in the UK, Europe and worldwide because food waste is associated with serious economic, environmental, and social impacts [1]. European statistics indicate that around 88 million tonnes or EUD 143 billion worth of food waste occurs in the EU every year (https://food.ec.europa.eu/safety/food-waste_en, accessed on 21 September 2022). The UK happens to be the largest contributor to this food waste contributing to 14.39 million tonnes (https://ourworldindata.org/grapher/food-waste-by-country-in-the-european-union, accessed on 23 September 2022). The European Food Information Council (EUFIC) estimates that around 931 million tons of food globally were wasted in 2019. According to UNDP [2], this amount increased to 1.3 billion tonnes of food waste in 2021, while nearly 2 billion people were left hungry and another 2 billion were obese. According to Eurostat, while an estimated 20% of the total food produced is lost or wasted, 36.2 million people cannot even afford a quality meal every second day, which emphasizes the social impact of food waste. The economic impact arises in two ways, (i) by preventing food waste, firms can sell more food and generate more revenue; and (ii) due to the amount of resources (water, nutrients, fertilizers, etc.) conserved, saved food waste is much more than the face value of the waste itself for the society. Further, significant carbon emissions will result in wasted food production, and the wasted food will emit more greenhouse gases in landfills, causing significant environmental impacts.

The literature on food waste sometimes uses a related term—food loss and waste. The term generally refers to "the decrease in mass (quantitative) or nutritional value (qualitative) of food—edible parts—throughout the supply chain that was intended for human consumption" (https://www.unep.org/thinkeatsave/about/definition-food-loss-and-waste accessed on 6 September 2022). Studies sometimes distinguish between the concepts of food loss and food waste (e.g., Ref. [3]). As per the above website, the former refers to the loss that takes place at production post-harvest, processing, and distribution stages of the food supply chain (which is usually considered unavoidable), while the latter term is the food that reaches the consumer but does not get consumed because it has been allowed to get spoiled (which is usually considered avoidable). However, modern literature (e.g., Ref. [4]) uses these terms interchangeably. This paper uses the term food waste consistently.

Supply chain issues are identified as one of the prominent causes based on a systematic literature review by Chauhan et al. [5]. Therefore, this paper focuses on food waste in the supply chain and deals with the use of technology in reducing food waste in agrifood supply chains.

Due to the economic, social, and environmental impacts caused by the food that is wasted, efforts must be focused on reducing this waste in all stages of the supply chain—from production to final consumption. Food waste is closely linked to several Sustainable Development Goals (SDG) of the United Nations (https://sdgs.un.org/goals, accessed on 6 September 2022). Increased food availability that results from reduced food waste will help achieve SDG 1 (no poverty), SDG 2 (zero hunger), and SDG 3 (good health and well-being). Food waste is directly linked to SDG 12 (responsible consumption and production), while it is relevant to several other SDGs.

SDG 12 focuses on responsible consumption and production for improved food security. It stresses achieving a good standard of living while reducing our ecological footprint. This goal emphasizes efficiency in all levels of production and consumption via efficient supply chains. Target 3 of SDG 12 focuses on halving per capita global food waste by 2030. This requires concerted action across all levels, from production, post-harvest processes, supply chains, retail, and consumer levels. Target 5 requires that waste generation is substantially reduced through prevention, reduction, recycling and reuse.

Lemaire and Limbourg [4] studied SDG 12 further, detailing the causes, solutions and research challenges related to managing food loss and waste. Among other categories, they highlighted the importance of efficient logistics/supply chain network design for reducing waste. Food quality tends to decline during supply chain operations, before and during production, storage in warehouses, transportation via trucks, planes, trains and ships, and consumption largely due to a lack of process control. Mena et al. [6] emphasized that inadequate process control, such as maintaining temperature and humidity levels in the food supply network, is a major cause of food waste, especially in cold chains. Appropriate quality control has been stressed as a key factor in reducing waste and improving the quality of transported food products [7]. Through appropriate mechanisms, Karki et al. [8] highlighted that food waste, food poverty and surplus food distribution could provide a win-win solution for the world. They further stress the role of the third sector in redistribution activities.

Modern digital technologies (also called as Industry 4.0 technologies) provide new opportunities to help food companies reduce waste in their supply chains [9–12]. For example, when food is transported in trucks, Internet of Things sensors can track the temperature, humidity and other relevant parameters in which the food is stored and send the details to cloud storage for remote access. If the food is stored in sub-optimal conditions (for example, when the storage temperature is above the maximum threshold), then decision-makers who remotely access the temperature can take appropriate action to correct the temperature rapidly. This will help prevent the food from becoming waste. In general, food companies are unaware of such promises of digital technologies. In recent years, some efforts have been made to promote digital technologies among food companies [12].

Despite the importance of reducing food waste and the efforts to promote the use of digital technologies for reducing waste in food supply chains, there has been very little effort to understand the motivations and barriers for food companies in using modern digital technologies for reducing food waste reduction. We attempt to fill this research gap by undertaking research activities by engaging with several food companies in Europe on the use of technology for reducing food waste. We share our experience from the last five years, as we worked with several European food companies on the use of technology for supporting food waste reduction (FWR). Therefore, the research questions for this paper are: (i) what are the motivations for food companies to use digital technologies for food waste in their supply chains and what are the challenges? (ii) what is the best business model for commercially exploiting the power of digital technologies for FWR? We find answers in this paper based on the action research methodology. The novelty of this study is in the appropriate use of technologies and the significance of these technologies can help save huge amounts of food waste. By understanding the motivations and challenges and analyzing business models, this paper contributes to achieving several SDGs.

This paper is organized as follows. The next section discusses the literature on FWR in food supply chains, emphasizing the use of modern digital technologies. We collected relevant data via action research through numerous meetings with relevant stakeholders, field visits, installations, and observations. The research approach and details of the data collection are presented in Section 3. The data analysis and findings are presented in Section 4. Our views on the motivations and challenges are presented in detail in this section. These findings are used to develop some future scenarios in the form of road maps. The last section presents a summary and conclusions.

2. Literature Review—Minimizing Food Waste in Agrifood Supply Chains

Food waste occurs in all parts of agrifood supply chains and can be minimized in various ways and approaches. Mena et al. [6] analyzed causes of food waste using case studies of selected supply chain networks of 15 food commodities (fruits, vegetables, and meat) and found that inadequate temperature control in supply chains was one of the most significant causes of waste of fruits and vegetables. For meat products, they stressed contamination, weather variations and damages in transit were found to be some of the main reasons for waste. Table 1 shows some prominent causes of food waste in agrifood supply chains.

Table 1. Some prominent causes of food waste in agrifood supply chains (Adapted from Refs. [6,13,14]).

Food Produc-tion/Abattoir	Processing and Packaging	Transport and Storage	Retailing	Consumption
• Food left in the field/abattoir • Food is eaten by birds and rodents • Choice of wrong harvesting time • Poor harvesting techniques • Lack of skilled workforce and other resources • Diseases and pests	• Inefficient processing/packaging techniques • Process losses during milling, cleaning, grinding, etc. • Inefficient quality management • Inefficient supply chain coordination and forecasting of demand.	• Improper and inefficient storage conditions • Inadequate control of temperature and other atmospheric/handling conditions • Lack of monitoring of atmospheric conditions • Inadequate infrastructure • Pests, disease, spillage, contamination and inadequate maintenance of temperature during shifting from one truck/warehouse to another • Natural drying out of food • Pilferage	• Inadequate aesthetics (e.g., food items not uniform) • Inappropriate use of food expiration date • Inefficient supply chain coordination and forecasting of demand resulting in unsold food	• Wasted in the fridge and not consumed while the food is fresh • Improper and inefficient storage conditions • Errors in cooking resulting in waste • Lack of portion size control • Lack of awareness of food waste and methods of valorizing waste

Table 1 covers the entire spectrum of food supply chains. However, the focus of this paper will be the first three stages shown in Table 1—farm, packaging, and transportation and storage. Table 1 shows that food waste in these stages is caused by various factors, including workforce, quality management techniques, processing techniques, supply chain coordination, and storage/transport conditions. Hence, efforts to reduce food waste should consider various options for avoiding the causes shown in Table 1. These options include technological and non-technological options [14–16]. For example, a skilled workforce can help improve efficiencies in farming/abattoirs, processing and transport efficiencies, and reduce waste. Early detection of pests and other diseases can reduce waste. Effective (non-destructive) quality control techniques can save food. There are technological options [15], especially by exploiting the power of modern digital technologies. This is the focus of this paper. These technological remedies are discussed in the next section.

Technological Options

Over the last few years, various digital technologies have been developed to increase the efficiencies of various stages of food supply chains [12,15]. This includes advanced digital technologies, for example, the use of drones and robots that can help improve farming efficiency. Modern scheduling, forecasting and supply chain collaboration tools can help improve operational efficiencies. Using the Internet of Things (IoT), sensors can help measure temperature and other parameters to maintain the freshness of food for longer. When the outputs from sensors are connected to the cloud and monitored via smartphone-based applications, timely warning signals can be sent to owners of food. In the case of a malfunction of temperature control systems, such a warning system can lead to rapid actions for reducing food waste. Other ways of using technology to support reducing food waste include real-time information-sharing using data collected with IoT networks, optimization of food delivery points based on real-time food-quality monitoring, and increased food shelf life using real-time cold-chain monitoring and control. For example, automated algorithms can help identify reductions in food quality sufficiently early, and food can be redirected to nearby demand points for sale before the food becomes a waste. Developing early detection algorithms based on sensor data and a platform linking suppliers and customers so that the nearest demand point can be located in the event of an unexpected reduction in food quality can also help make use of food that would otherwise become a waste. Further, when the data from IoT sensors are monitored and combined with externally available data (such as local weather) and the resulting big data is analyzed using modern data analytics techniques, more detailed understandings of the patterns and causes of food waste can emerge, leading to better solutions to reduce food waste.

Table 2 provides a brief overview of some important modern digital technologies and their use to support food waste applications. Please note that Table 2 provides a long list of prominent modern digital technologies, but not all of them are considered in the subsequent sections of this paper.

Table 2. Prominent modern digital technologies and their applications in food supply chains.

Technology	Main Characteristic	Applications in Food Supply Chains	Application to Support Food Waste
Radio frequency identification (RFID)	Auto-identification technology with several business uses. It uses radio frequency (RF) waves to identify, track and locate individual physical items.	Traceability has been one of the most important applications of RFID [17]; for instance, the fish food supply chain is an important area where traceability plays an important role. It also helps to ensure food safety.	Li et al. [18] considered the application of RFID in food safety.
Advanced robots	Robots, including drones, are being deployed in agriculture, manufacturing and delivery and are providing immense benefits. These robots can help supply chains in picking, palletizing, and unloading. They can transform businesses to help them respond faster, safer, and more productively to the external environment. They can also help during pandemic situations (e.g., COVID-19) when human beings cannot move around freely.	Applications of drones during a flood in airdrops [9].	In Ref. [19], robots in agriculture and reducing food wastage and their prospects and impacts are discussed.

Table 2. *Cont.*

Technology	Main Characteristic	Applications in Food Supply Chains	Application to Support Food Waste
Blockchain technology	It is a collection of records, called 'blocks', across several computers linked in peer-to-peer networks. Blockchain provides security and transparency as, due to the networking feature, it cannot be corrupted. Other key characteristics of blockchain technology are decentralization, anonymity, persistence, audibility, and resistance to modification or changes to the data.	Tiwari [20] demonstrated the application of blockchain in the agrifood supply chain.	Refs. [21,22] researched the impact of blockchain technology in reducing food waste.
Three-dimensional printing (3D printing) (or additive manufacturing or rapid prototyping).	They are currently being used extensively in automotive, aerospace, defence, consumer products, industrial products, healthcare, and architecture. This technology increases production flexibility, reduces waste, decentralizes production and helps reduce complexity in businesses.	3D printing is introduced as an emerging technology to support sustainable supply chain and environmental quality management [23].	Prakash et al. [24] discussed the future of 3D food printing in the food industry; This study contains 3D food printing technologies and their working mechanisms within a broad spectrum of application areas, including the development of soft foods and sweets design. It provides a unique guide to help correlate supply materials (edible inks) and the technologies (laser-based) used during the construction of 3D shapes.
Internet of Things (IoT) technology	IoT devices measure some characteristics in an application and are connected to the cloud so that the device's reading can be externally monitored for business decisions. These devices range from smartphones, wearable devices, industrial equipment, appliances, and anything else that collects and transmits data via the internet.	Yadav et al. [17] investigated and developed an IoT-based system in food supply chains. Verdouw et al. [25] provided an IoT-based reference architecture for food supply chains.	A review of efficient food waste management systems using IoT is available in [26]
Cloud Computing Technology (CCT)	CCT is a cost-effective way to run applications, store data, and accomplish other IT tasks. It can help improve internal efficiencies, including capital investment savings, simplified operations, scalability, improved information visibility, sustainability, and faster deployment.	Singh et al. [27] studied big data CCT for low-carbon supplier selection of beef food supply chains. Mustapha et al. [28] reviewed sustainable agriculture development roles of CCT, IoT, and artificial intelligence.	Funchal et al. [29] explained the CCT-enabled integration of IoT applications for food waste reduction.

Table 2. *Cont.*

Technology	Main Characteristic	Applications in Food Supply Chains	Application to Support Food Waste
Big data analytics and artificial intelligence (BDA-AI)	Internet of Things devices and other digital technologies create a massive amount of data, often on a real-time basis. Advanced analytics, Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning technologies have been designed to make use of this big data for developing important business insights and help in crucial business decisions (e.g., on product designs, manufacturing, distribution, and sales).	Misra et al. [30] investigated IoT, BDA, and AI in food supply chains.	Sharma et al. [31] discussed sustainable innovation in the food industry through AI and BDA.
Virtual Reality (VR), Augmented Reality (AR) and metaverse	They are adding layer upon layer of digitized overlaid information to the world around us, making it rich, meaningful, and interactive. They are useful to businesses in remote working and collaboration, maintenance issues, safety warnings, employee/customer digital experience, and more.	Morella et al. [32] demonstrated the application of VR in food supply chains.	Seiler et al. [33] studied reducing food waste with VR.

3. Methodology

This paper focuses on using innovative modern digital technologies to improve supply chain resource efficiency and reduce food waste in food supply chains. It draws heavily on our work in a transnational–European territorial cooperation project co-funded by the Interreg North-West Europe Programme [12].

Due to the extensive involvement in the preliminary discussion, implementation, making observations, data collection, and analysis, our approach to this research could be termed Action Research [34,35]. Erro-Garcés and Alfaro-Tanco [36] defined action research as research applied in business and management and involves researchers and organizations who collaboratively undertake research in a practical setting. The research and the action become part of the results of action research. Erro-Garcés and Alfaro-Tanco [36] further cited Ref. [37], who claims that the collaboration increases the authenticity and trustworthiness of the results. Accordingly, researchers (academic experts) and practitioners (agribusiness organizations) have worked together to learn more about the issues related to the implementation of modern digital technologies (MDT) in agribusiness organizations. Our action research involves the intervention and transformation in a dynamic process through the collaboration of researchers and practitioners in a business setting. The learnings discussed in the next few sections are the results of our action research.

The central part of the action research methodology is the demonstrations of the MDT in multiple agribusiness organizations. Figure 1 illustrates the approach adopted to work with agribusiness organizations.

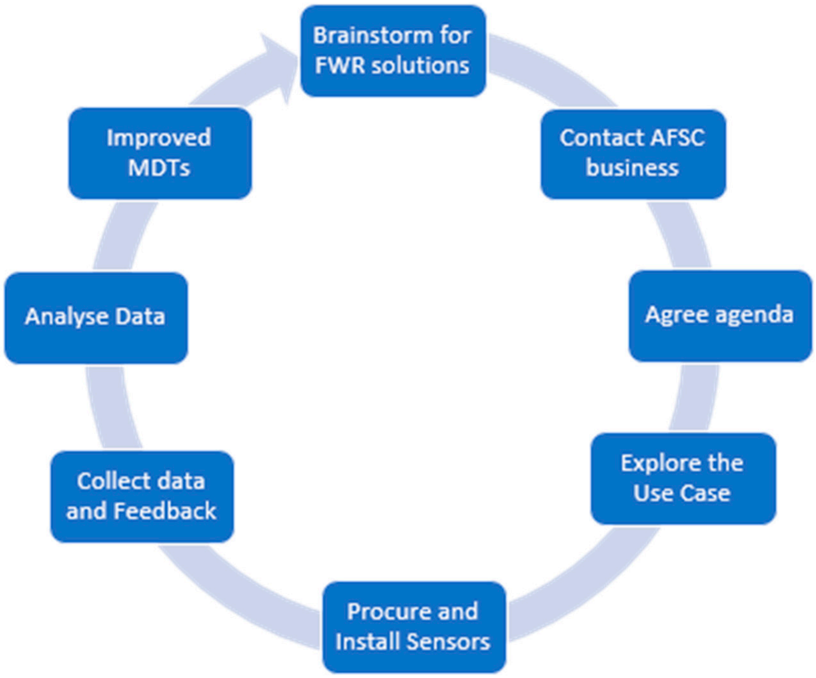

Figure 1. Approach adopted to collaborate with relevant agribusiness organizations.

Our efforts in reaching out to agribusinesses resulted in technology demonstrations in multiple food businesses across Europe. The demonstrations primarily focused on food production and transport/storage stages of the food supply chains. Table 3 provides more details of the technology demonstrations. All the demonstrations used IoT, CCT, and BDA-AI.

Table 3. A listing of Technology Demonstrations of modern digital technologies for reducing food waste in European businesses.

TD Number	Stage of the Supply Chain	Country	Food Waste Issue	MDT Deployed	Solution/REMARKS
1.	Food processing in an abattoir	UK	Meat waste due to un-uniform temperature distribution in dry-aging chambers (fridges).	IoT temperature and humidity sensors located at multiple points to monitor uniform temperature distribution, and CCT and BDA-AI. Alerts via a smartphone and email.	Ensure uniform distribution of air in the chamber. Send warning alerts if needed.
2.	Food processing in an abattoir.	Republic of Ireland	Meat waste due to un-uniform temperature distribution in dry aging chambers (fridges).	IoT temperature, humidity, and pressure sensors located at multiple points to monitor uniform temperature distribution, and CCT and BDA-AI. Alerts via a smartphone and email.	Ensure uniform distribution of air in the chamber. Send warning alerts if needed.

Table 3. *Cont.*

TD Number	Stage of the Supply Chain	Country	Food Waste Issue	MDT Deployed	Solution/REMARKS
3.	Food storage in a frozen food company	UK	Food waste due to inadequate temperature in fridges	IoT temperature sensors located in fridges to monitor temperature, and CCT and BDA-AI. Alerts via a smartphone and email.	Send alerts if the temperature is not maintained within a pre-specified threshold.
4.	Milk transportation	UK	Food waste due to inadequate temperature during transport	IoT temperature sensors located in transport options to monitor the temperature, and CCT and BDA-AI. Alerts via a smartphone and email.	Send alerts if temperature is not maintained within a pre-specified threshold.
5.	Transport	UK	Food waste due to temperature anomalies during transport	IoT temperature sensors located in fridge and freezer of the van to monitor temperature, and CCT and BDA-AI. Alerts via a smartphone and email.	Send alerts if the temperature is not maintained within a pre-specified threshold.
6.	Transport	The Netherlands	Food waste due to the inadequate volume of icepacks used during transport	IoT temperature sensors located in the grocery transport crates to monitor the temperature, and CCT and BDA-AI.	ML model to predict quantity of ice required to maintain temperature given the weather and journey length.
7.	Storage and transport in multiple stages of the supply chain	Luxembourg	Food waste is due to temperature abuse at the transport and storage stage of the supply chain.	IoT temperature and humidity sensors located at each stage of the supply chain (farm, transport, storage), and CCT and BDA-AI.	ML model for early warning of product degradation given temperature.
8.	Storage and transport in multiple stages of the supply chain	Germany	Quality differences between two different producers. Wastage occurs more quickly from one than the other.	IoT temperature, humidity, and VOC sensors located in transport options, and CCT and BDA-AI.	ML model for early warning of quality warning given temperature, humidity, and VOC.
9.	Storage	The Netherlands	Food waste due to pressure abuse at the storage stage of the supply chain	IoT pressure sensors located at a storage facility, and CCT and BDA-AI. Alerts via a smartphone and email.	Send alerts if pressure is not maintained within a pre-specified threshold.
10.	Processing—wine manufacturing	UK	Food waste of raw material when the right temperature and flow are not maintained in the production process.	IoT temperature and flow sensors monitor temperature and other relevant parameters during production.	Discontinued after initial discussion.

Table 3. *Cont.*

TD Number	Stage of the Supply Chain	Country	Food Waste Issue	MDT Deployed	Solution/REMARKS
11.	Production—raising cattle	UK	Food waste due to unacceptable quality of meat.	Motion sensors on cattle.	Discontinued after initial discussion.
12.	Transportation	UK	Food waste in international transport.	IoT temperature sensors located in transport options to monitor the temperature.	Discontinued because of the difficulties of internet connectivity in international air transport.
13.	Food production, storage and transport	Germany	Food waste due to temperature anomalies during transport	IoT temperature sensors located in transport options to monitor the temperature.	Discontinued after initial discussion.

Of the companies approached, nine agreed to participate in technology demonstrations. The discussion in the rest of the paper is based on these nine demonstrations. Two papers [38,39] published in the same special issue as this paper described two of these nine technology demonstrations in detail. As per Figure 1, the next stage was to procure and install the sensors. The use case of the company, defined in Table 3, determined what modern digital technology was most appropriate for the successful execution of the technology demonstration. For example, if the company was focused on monitoring the storage stage of the food supply chain, a LoRaWAN (Long Range Wide Area Network) sensor could be deployed, which are widely known for its long transmission range and low power consumption, making them very popular for IoT applications. While these sensors have the benefit of minimal maintenance and upkeep due to their long battery life, they are best suited for fixed locations as they require a LoRa network to connect to the cloud. In the UK, this network is generally facilitated by privately owned gateway devices, and the coverage is very sporadic. Alternatively, if the company was focused on monitoring at the transport stage, GPRS loggers could be used, operating on the telecommunication networks already in place by mobile phone operators. While GPRS loggers, therefore, benefit from remote cloud connectivity, essential while monitoring cargo during transportation, they also have more demanding energy requirements. This results in a monitoring system that requires more maintenance in the form of battery replacements from the company.

4. Results—Insights on the Motivations of Businesses

As specified in Figure 1, the first step in reaching out to potential businesses is to prepare posters and flyers to bring out the benefits of FWR. Multiple stakeholders, stated below, were consulted in preparing the posters: IoT sensor technology firms, agribusiness SMEs and companies, farmers, processors, and wholesalers involved in FWR in food supply chains, public bodies and NGOs to help reach potential stakeholders, big data agritech firms, and research and policy institutions.

4.1. Benefits to Organizations in Food Supply Chains

Interactions with these stakeholders have resulted in interesting findings, depicted via the infographics shown in Figure 2.

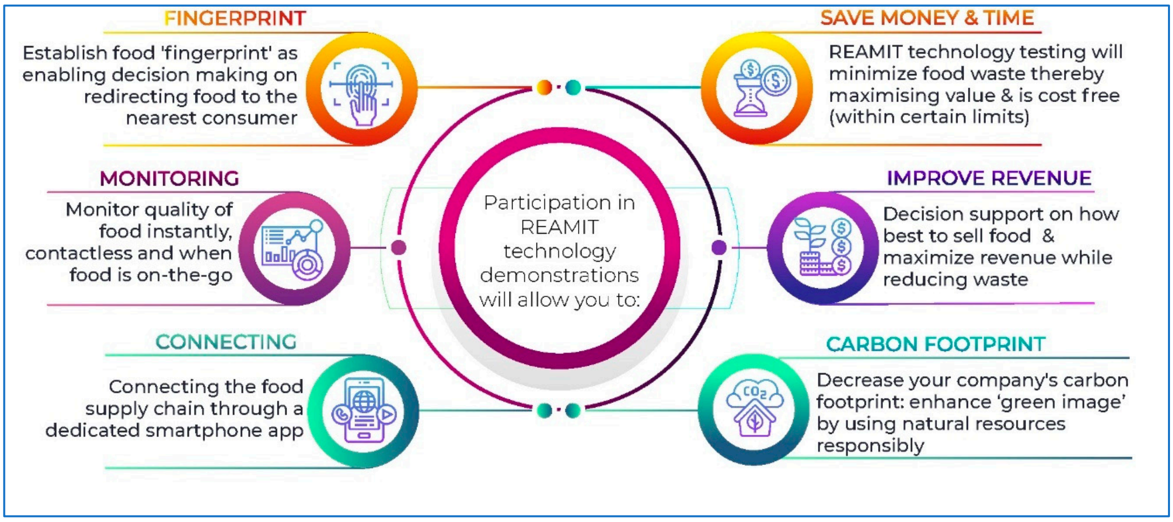

Figure 2. Potential benefits to agribusiness organizations in engaging in FWR using modern digital technologies. Source: Ref. [12]. (Reprinted with permission from authors of Ref. [12])

As can be seen in Figure 2, a technology-based approach to reducing food waste can help food companies in multiple ways. They will get access to valuable sensor technology to measure their food waste fingerprint. If necessary, the food which would otherwise go to waste can be redirected to needy people nearby. This helps measure their carbon footprint as well. Wi-Fi-enabled IoT sensors can connect to systems via the internet for remote monitoring. This will avoid frequent manual intervention and hence can save money and time. Reducing food waste would mean a better carbon footprint. Table 4 provides an overview of the key benefits and the associated impact areas.

Table 4. An overview of the impact and associated key benefits.

Impact Dimension	Key Benefits
Economic	• Increased revenue as food avoided being wasted generates more revenue. • Enhanced competitive position for the company in the market • Reduced costs by using intelligent solutions with the decision support systems • Improved energy efficiency • Enhanced green image/company reputation for being very active in preventing food waste • Optimized the use of resources during food transportation (e.g., energy) by monitoring and optimizing the route of the vehicles
Societal	• Reduced food wastage and increased food availability can help those in need of food • Improved quality of fresh food delivered to customers' homes • Improved consumer satisfaction (reduce consumers' complaints) • Increased volume of food delivered to consumers • Due to the amount of resources (water, nutrients, fertilizers, etc.) used in producing food, waste saved is much more than the face value of the waste itself for the society
Environmental	• Decreased volume of wasted food in each route/day/week/month • Decreased carbon footprint • Avoidance of significant carbon emissions will result in the production of food that is wasted • Avoidance of greenhouse gas emissions that would have been emitted had the food been sent to a landfill

We interacted with multiple food companies in Europe for more than years on using modern digital technologies in FWR in their organizations. While food companies recognized the need for FWR and to improve their carbon footprint, not all of them were prepared to engage with using modern digital technologies for FWR. The food companies we contacted did not have prior experience using technologies, such as the Internet of Things sensors and big data for real-time information on the quality parameters (such as temperature and humidity). Some of them have been using thermometers and refrigerated trucks for transporting food but did not attempt to track quality parameters in real-time. Thus, if the refrigeration system does not work properly, they will only know this problem when the truck reaches its destination, and by then, the food will have become a waste. The companies did provide some examples of food loss in this way. Hence, they generally valued the use of Internet of Things sensors and other technologies so that quality parameters could be tracked in real-time. Detailed information on the technology demonstrations in at least two food companies has been discussed in other papers in this special issue (Ref. [38] for food—human milk transport and Ref. [39] for food storage). While a detailed discussion of our experience on all the technology demonstrations is beyond the scope of this paper due to lack of space, the discussions in this section are based on our experience in all the technology demonstrations.

It must be noted here that software also plays an important role in ensuring that the data from sensors are collected in the cloud and analyzed via dedicated software to identify anomalies and send alerts to food companies. Technology providers usually handle this software. Food companies are given access to a user-friendly graphical interface called a dashboard. The detailed case studies show more details of the dashboards [38,39].

Our interactions revealed that while there were several factors for companies to use modern digital technologies for FWR, there were also some issues that would prevent food firms from using modern digital technologies. In the next few subsections, we present our understanding of these motivators (drivers) and challenges (barriers).

4.2. Motivations

Based on our experience working with these technology demonstration cases, the following prominent motivators that would encourage them to use technology for FWR are identified.

4.2.1. Food Quality

Several firms realized that using technology for continuous monitoring is a very useful way of maintaining food quality while benefiting from FWR. Several food companies engaged in TDs are reporting that they do not incur food waste anymore after the sensor technology is installed and continuously monitored. Technologies have primarily helped these companies improve the quality of their produce, as they can track performance in terms of quality-related variables. Since improving quality can help in multiple ways (e.g., Ref. [40]), these firms enjoy improving productivity, reduced waste, and increased revenue via higher prices.

4.2.2. Reliability

Food firms have experienced increased reliability of their food processing systems due to the measurement of quality parameters (e.g., temperature and humidity) and continuous monitoring of these parameters. Potential failure issues can be better predicted with these real-time data for increased reliability of their production processes [41].

4.2.3. Legal

Food safety regulations are an important reason companies try to use modern digital technologies to continuously monitor food quality to prevent waste in their organizations. Several companies cited the regulatory requirement on food quality as a main reason for using technology, supporting FWR. Specifically, the Hazard Analysis & Critical Control

Point (HACCP) directive, introduced in the EU in the 1990s and modified in subsequent years, expects EU food business operators to implement and maintain a permanent procedure or procedures based on the HACCP principles. The plan should protect food against contamination with bacteria, fungi, viruses and parasites. Maintaining correct atmospheric conditions (temperature, humidity, etc.) that would keep the shelf life of food long enough could be a good plan, which is better served using IoT sensors and other technologies, which would, in turn, help avoid FWR. Thus, some organizations decided that installing sensors can help their adherence to food safety regulations while at the same time helping them in FWR, as echoed in the literature (e.g., Ref. [42]).

4.2.4. Green Image

Engaging in activities that create waste can be used by firms to project a green image and competitive advantage [43,44]. They can use these efforts to show that they are contributing to improving overall sustainability and helping to save the planet. Explicit associations with established food charities can also be a good motivator for a green image.

4.2.5. Pressures from Stakeholders

Commitment from top management and commitment from employees plays a strong role in reducing food waste. Other downstream supply chain partners, by virtue of their position as customers, also exert pressure on reducing food waste. Pressures from other stakeholders, such as the media or the general public, are apparent, considering the higher emphasis on reducing food waste and adopting sustainable food practices in modern days compared to a few decades earlier. These observations are consistent with the tenets of the stakeholder theory [45].

4.2.6. Economic Factors and Survival

The economic dimension of the additional value derived from the food that has been prevented from going to waste is an important motivator for businesses to use modern technologies. In addition, the reduction in waste disposal costs due to FWR led to more cost efficiency. Some firms realized that their quest to reduce food waste has helped them find new ways to improve the operational efficiency of their operations, which in turn further reduced costs. The economic dimension manifested in an opposite way when food companies prioritized their survival and were hesitant to engage in innovative technologies during the COVID-19 pandemic, even though they knew the benefits of working on the project. This is consistent with similar observations in the literature [46]. In principle, it is important to ensure that the costs invested in technologies for FWR should compare favorably to the cost of food waste saved. The economic analysis is not so straightforward considering the multiple benefits (discussed above) of these technologies for the companies. However, it is important to ensure that the resources spent in producing and installing these technologies should be much lower than the resources saved by the avoided food waste avoided, which can be confirmed using life cycle analysis (LCA).

4.3. Challenges

While the above motivators did help us reach out to more companies for successful technology demonstrations, some challenges emerged. These challenges revolved primarily around the collection of sensitive data using IoT sensors.

4.3.1. Data Security, Data Sharing, Threat from Hackers

As explained previously, one of the first steps in our approach to technology demonstrations is to assure the companies that their data will be kept safely and securely. In spite of this promise, we found that data sharing and security issues could be important barriers on why companies might not be willing to use technology. For example, data that could help measure waste in their system can be potentially used to project the level of inefficiency, which can affect the company's brand image. This fear was a main barrier in this context.

The threat of hacking contributed to this challenge. Shared sensor data to multiple entities in the supply chain (e.g., data analytics companies) could create opportunities for malicious agents to disrupt the food chain via cyberattacks. It is important to ensure that suitable data management plans (e.g., blockchain) are available to minimize data security issues.

4.3.2. Privacy

The perception that using modern digital technologies might infringe on the privacy of potential users was witnessed in our discussion with some food companies. For example, there was hesitation from drivers of trucks to install a gateway in their cabins due to privacy concerns and also other concerns such as exposure to radioactivity. In another case, some drivers were not happy to track the location of their vehicles, as it was deemed an invasion of privacy. This adequate consideration of privacy issues could pose challenges to large-scale adoption of the technologies [47].

4.3.3. Technological Challenges

Though significant technological developments helped produce relatively inexpensive systems for measuring and monitoring quality parameters, our technology demonstrations did bring more challenging situations that tend to extend the current capabilities. For example, one company wanted to track the temperature of fruits during international flights, which could not be completed cost-effectively with the current technologies available in the market.

4.3.4. Trust Issues

A general negative perception from some companies on any IT projects could be seen during the interactions [48]. Given that several IT projects overpromise and under-deliver, we also witnessed the negative perception during our work's early stages. However, as we could show successful TDs over time, trust issues became more positive.

5. Exploring the Future of Use of Modern Digital Technologies for FWR—Business Models, Sustainability Plans and Roadmaps

In this section, we use our experience with multiple food companies to explore the future development of modern digital technologies for FWR.

5.1. Business Models for Supporting the Use of Digital Technologies in Food Supply Chain Companies

In the long run, large-scale commercialization of modern digital technologies for supporting food waste depends on developing suitable business models. Business Model (BM) is a term normally used to understand how commercial entities can exploit a unique capability to address a business need and develop appropriate revenue mechanisms to survive in the marketplace [49]. The literature on BMs provides multiple definitions for the term [49–51]. While addressing the business needs of a firm's internal and external stakeholders, business models need to clearly identify the underlying value proposition, value delivery, value creation, and value capture [52,53]. Nine building blocks of a typical BM have been specified by Osterwalder and Pigneur [53]. The nine building blocks are value proposition, customer segments, customer relationships, channels, key partners, key activities, key resources, cost structure, and revenue streams. However, modern discussions of a typical BM usually consider four more prominent of the nine blocks—value proposition (the value embedded in the products/services offered by the firm), supply chain (the relationships with suppliers), customer interface (the relationships with customers); financial model (costs and benefits and their distribution among stakeholders).

An empathy map canvas [54] is sometimes used to explain business models. Standard versions of the canvas (e.g., https://gamestorming.com/empathy-mapping/ accessed on 27 September 2022) outline some of the building blocks identified by Osterwalder & Pigneur [53]. Figure 2 gives an example of an empathy map canvas for the business model based on modern digital technologies for FWR in food supply chains.

Figure 3 explains many aspects that would make a business (Business A) engaged in using technology for FWR in food supply chains commercially viable. Business A serves food producers and supply chains to help FWR, the customers. The business highlights that there must be an approach to measure waste generated and reduce food waste in their operations. The strong point is that all businesses, including food businesses, are aware of the need to reduce waste and improve sustainability. In addition, existing governmental policies (e.g., the goal for net-zero carbon emissions by the UK government) also provide additional incentives for food companies to engage in FWR. Business A should inform their potential customers about the win-win strategy; that is, reducing food waste helps them economically (increased revenues and reduced waste disposal costs) but also help them comply with regulations and improve their green image and sustainability plans. Unfortunately, Business A's customers (who are food companies) consider waste in their supply chain unavoidable and are internalizing it. However, Business A should demonstrate that newer developments in modern digital technologies can help reduce this waste by developing demonstrations and use cases.

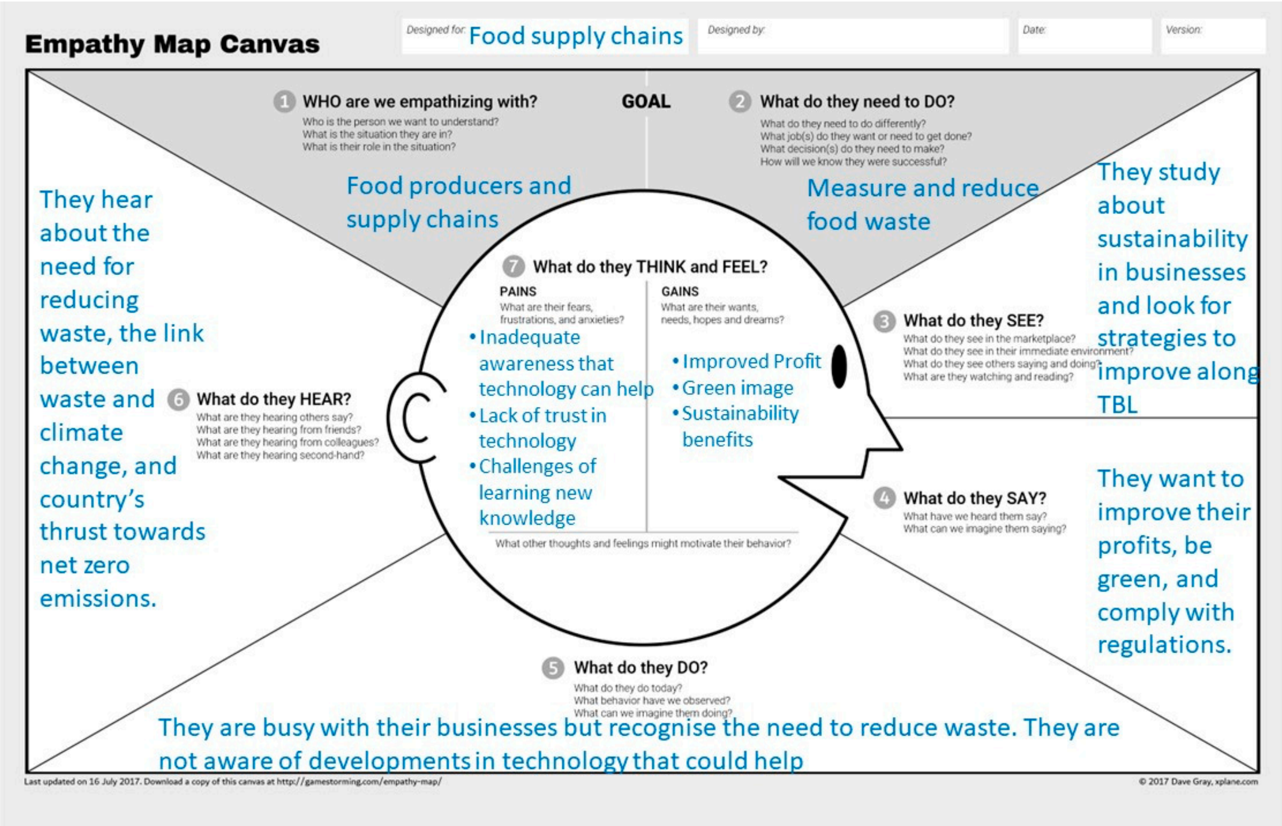

Figure 3. Empathy canvas outlines the business model of using modern digital technologies for FWR in food supply chains.

The literature on business models distinguishes between traditional and newer business models [55]. While traditional business models rely on incremental innovations, new business models are based on radical and disrupting innovations. Sometimes business models dealing with sustainable solutions are called sustainable business models, while business models focusing on minimizing waste and reusing waste in other processes for zero waste are called circular business models [49]. Due to the focus on sustainability and FWR, any business model developed using modern digital technologies will belong to the categories of sustainable and circular business models. In general, Industry 4.0 technologies [9,10] belong to disruptive or radical innovation category, and hence the business models using modern digital technologies are newer business models.

The literature outlines at least four categories of sustainable business models [49]—circular business models, social enterprises, the bottom of the pyramid solutions and product service systems. Of these, a profit-making business model that uses technology for FWR in food companies can be termed a circular business model. Servitization-based business models (also called product-service business models) rely on developing a tangible product but selling the integrated product-service offerings to improve customer experience. While Business A can sell simple hardware, such as IoT sensors, it will reap better rewards if it can link the sensors to CCT and BDA-AI and offer the integrated solution to customers. This vertical integration will help customers enjoy the service better and improve revenue generation. Business A can offer a subscription-based revenue model that measures the extent of use by customers and charges them accordingly.

A successful business model should specify at least four major dimensions—value proposition, value delivery, value creation and value capture [51]. The business model that uses technology for FWR can be characterized in terms of these dimensions, as shown in Table 5.

Table 5. Dimensions of a business model for technology companies that support the use of technology for FWR in food supply chains.

Major Dimensions	Sub-Categories	
Value proposition	Products	Smart hardware such as sensors, cloud infrastructure and software for BDA-AI.
	Services	Timely alerts of any deviation from optimal conditions for food storage.
Value delivery	Target customers	Food companies are conscious of quality and sustainability.
	Value delivery processes	Timely alerts will help avoid food waste, connecting potential nearby demand points when there is a risk of food becoming waste soon. Mobile application for ease of operation. More efficient food production, logistics, quality control and storage opportunities for food companies.
Value creation	Partners and stakeholders	Food supply chain companies, companies manufacturing IoT sensors, CCT and BDA-AI software, data-driven decision-making capabilities.
	Value creation processes	Measurement and continuous monitoring of storage conditions, such as temperature and humidity, connecting to potential nearby demand points when there is a danger of food becoming waste soon.
Value capture	Revenues	Sale of hardware and subscriptions. Dynamic pricing, pay-per-use and performance-based revenues.
	Costs	Hardware such as sensors, cloud infrastructure, software costs for BDA-AI and staff costs, costs of training and support, and maintenance costs

5.2. Sustainability Plans

This section looks at the sustainability impacts of using technology for FWR and develops a plan for future large-scale diffusion that would help avoid significant quantities of food waste. As highlighted earlier, the concept of sustainability can be viewed in multiple dimensions—economic, environmental and social. A business that uses technology for FWR can contribute in terms of all these dimensions.

Economic dimension: The economic impact of food waste is well-known in the literature. As highlighted in the introduction, huge amounts of food are wasted across nations, continents, and, in fact, the globe (1.3 billion tonnes of food in 2021 as per UNDP [2]). Literature highlights that food waste occurs in all stages of the food supply chain—production, processing, transport, storage, retail, and consumer end. There is scope for reducing food waste in all of these stages. Mena et al. [6] estimated the level of food waste in various stages in the supply chain for fruits and vegetables and meat products. For example, waste occurs during grading, storage, packing and retail for fruits and vegetables, while waste occurs for meat products during slaughtering, processing, packing and retail. They also highlight that improper temperature and humidity conditions during storage and transport are crucial causes of food waste in food supply chains. Other studies, such as [56], have highlighted that supply chain stages account for as much as 28% of food waste that occurs during the supply chain stages (food services, production, wholesale, and retail). Unlike food waste in households, food waste at supply chain stages occurs primarily due to improper storage conditions. It hence can be tackled by continuously monitoring the storage conditions using MDTs. Even if one assumes that about 10% of the food waste in supply chain stages can be avoided using MDTs, it amounts to huge savings in food waste reduction. Thus, the scope for the positive economic impact of using technology for FWR is huge at 10% of 28% of 1.3 billion tonnes per year or 36.68 million tonnes of food per year.

Social dimension: As mentioned earlier, food waste has significant social impacts too. While a significant amount of food is wasted by a section of the world's population, nearly 2 billion people are hungry [2]. Thus, if the food that normally gets wasted is avoided and the resulting excess food is sent to feed those in need will help avoid several social problems (e.g., crime). We highlight the social benefits of saving food waste here, though we recognize the logistical complications involved in feeding hungry people with the food waste avoided. Another social benefit of saving food waste can also be highlighted. If food is wasted, all resources (e.g., water, labor, electricity and fertilizer) that were used in producing the food would also become waste. This will result in additional adverse social impacts.

Environmental dimension: Environmental impacts of food waste have been well-researched in the literature. Food waste adversely impacts the environment in at least two ways. (i) Wasted food that ends in a landfill will be a source of greenhouse gas emissions. It has been estimated that greenhouse gases from food waste are approximately 4.4 gigatons (Gt) of carbon dioxide equivalents (CO2 e) per year. Comparisons with national emissions have been made (that is, if food waste were a country, it would rank as the third-highest emitter after the United States and China) (Ref. [57], quoting data from Emissions Database for Global Atmospheric Research at https://data.jrc.ec.europa.eu/collection/edgar) (accessed on 01 December 2022).

There are several ways of valorizing waste [56]. For example, food waste can be used as feed for animals, sent to anaerobic digestion to produce biogas or sent straight to the landfill). While these activities help reduce the impact of food waste once occurred, the best way to avoid the adverse impact of food waste is to prevent it from occurring. For example, Parry et al. [56] estimated that nearly 3090 kg of CO2e can be avoided if food waste is redistributed to people from manufacturing/retail. This value is much higher compared to other waste disposal options. For example, using food waste as feed for animals would avoid only 220 kg of CO2e in comparison.

Thus, modern digital technologies can play a crucial role in FWR by ensuring appropriate storage conditions (temperature and humidity) in food supply chains. By measuring these parameters, a warning signal can be sent when these parameters exceed acceptable storage conditions and thus help in appropriate immediate corrective actions. By ensuring optimal storage conditions, technology can thus be used to avoid significant carbon emissions. Using life-cycle emissions, we estimated that about 0.84 tonnes of CO_2 can be avoided every time a warning alert is sent for fruits/vegetables or frozen food, while as much as 107 tonnes of CO_2e can be avoided in meat industries for each warning signal. In this special issue, they will be explained in greater detail in subsequent papers.

5.3. Roadmaps

We illustrated in this paper that modern digital technologies could play a crucial role in FWR in food supply chains. By continuously monitoring food environment conditions (temperature, humidity, etc.) along the supply chains, sensors can help ensure that food is stored and transported in optimal conditions during supply chain processes. Warning signals in the case of non-optimal conditions can be used to rapidly identify problems and retain optimal storage conditions. Significant food waste and equally significant carbon emissions can thus be avoided.

However, there are challenges to employing technologies for FWR. As the business models have highlighted, companies specializing in technology must make efforts to publicize the value of these technologies for FWR. We have so far approached a handful of food companies and demonstrated the benefits of using technology for FWR. However, significant efforts are required to scale up these technologies.

The following roadmap strategies are recommended to achieve a substantial target of reducing food waste.

1. Keep abreast of the latest developments in modern digital technologies and utilize the most cost-effective technologies.
2. Showcase a number of demonstrator applications of the use of modern digital technologies for FWR in selected companies. Bring out all the elements of a sustainable business model (including the value proposition, creation and delivery dimensions).
3. Use the success of the demonstrators to reach out to more food companies. Explain the food waste saved, the carbon emissions avoided, and the social benefits derived from each demonstration case.
4. Reach out to more food companies. There is potential to reduce 107 tonnes of carbon emissions by working with meat companies each time a warning signal is sent. This can translate to significant tons of carbon emissions over a year. By reaching more meat companies, this saving can be much larger. For example, if 100 such companies are reached in one year, there is a potential saving of 10,700 tonnes of carbon emissions per year. Therefore, it is imperative to scale up the technology adoption by involving more companies in the next few years and save as much carbon emissions as possible.
5. Work with policymakers to incentivize food companies to use modern digital technologies to reduce food waste in their supply chains. This can be done, for example, by formulating guidelines, policy briefs, regulations, taxes and incentives and via appropriate labeling mechanisms confirming 'pro-active food waste reduction status'. This will encourage much wider deployment of modern digital technologies in food supply chains and will help avoid more food waste and reduce more carbon emissions in the future.

6. Conclusions

This paper has demonstrated the value of modern digital technologies in helping to reduce waste in food supply chains. Based on the experience gained in reaching out to food businesses across northwest Europe over the last four years, it analyzed the motivations and challenges for companies, discussed potential business models for supporting the use of digital technologies in food supply chain companies and highlighted the roadmaps for avoiding a significant amount of food waste and carbon emissions. For example, improved food quality and the ability to meet some legal requirements are important motivations, while there are challenges in the form of trust and security issues. Technology companies can create value for food companies around reduced waste via timely alerts. In return, they can generate revenues by charging food companies for the sale of hardware and subscriptions.

The paper has theoretical and practical implications. This paper contributes to the theory and practice by discussing the motivations and challenges. Theoretical implications arise because the motivations and challenges provide an opportunity to utilize established theories, such as the technology assessment models, technology–organization–environment theory, the resource-based view, t institutional theory, and transaction cost theory for further understanding how food firms can be supported towards the cause of food waste reduction [58]. Practical implications arise because this study provides important factors (quality issues, legal issues, trust issues, etc.) that managers of food firms need to be aware of for engaging in the use of technologies for FWR. The roadmap described in Section 5.3 provides more practical implications on working with food companies and policy-makers.

It is hoped that more companies will take advantage of the power of technologies to help reduce waste in food supply chains, thereby supporting a number of the UN's sustainable development goals. The field of digital technology is continuously evolving. It is quite possible that the trust or security issues can be addressed by more promising technologies (e.g., blockchain) or by hitherto undiscovered technologies. Technology companies should keep abreast of the latest technological developments and support food companies to reduce food waste.

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Institutional Review Board Statement: The study was conducted after gaining ethical approval (ref BMRI/Ethics/Staff/2018-19/005) from the University of Bedfordshire, UK.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: REAMIT project and case-study videos are available at www.reamit.eu (accessed on 01 December 2022).

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