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An Exploratory Study on the Opportunities of Using AI for Food Waste Reduction

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Abstract

Food waste has global economic, environmental and social implications, and hence tackling food waste provides significant opportunities to achieve several Sustainable Development Goals (SDGs). The literature has already documented several promising technological opportunities to help food firms reduce waste in their supply chains. Real-time monitoring of food supply chains with Internet of Things (IoT) sensors is now well documented, particularly for storage and transport, yet the data these systems generate are mostly used for simple threshold alerts rather than learning. Evidence on artificial intelligence (AI) for food waste reduction is growing but remains concentrated in hospitality and retail and is largely conceptual. With binding EU food waste targets for 2030 now in law, food businesses need practical routes from monitoring data to AI-supported decisions. This paper explores the potential of artificial intelligence (AI) to address food waste challenges, using action research and drawing on extensive collaboration with industry partners across the agri-food supply chain in North-West Europe. Our data were collected over a period of 2 years using observations and interactions with food supply chains during the execution of a large-scale European-funded project. This paper describes several opportunities for using AI in detail. Our research illustrates the multi-disciplinary challenges and the promise of AI approaches in reducing food waste, thereby achieving several SDGs. We develop several research objectives to support future researchers.

Keywords: food waste; IoT sensors; big data; analytics; artificial intelligence

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1. Introduction

Food waste is a global problem. Nearly 30–40% of the food we produce gets wasted [1]. Food waste has enormous social, environmental and economic implications [2]. Due to this, reducing food waste helps generate tangible impacts, including reducing greenhouse gases (GHG), improving food security and achieving a number of Sustainable Development Goals (SDGs) (e.g., [3]). In response, the United Nations and governments worldwide have prioritized reducing food waste. It has been estimated that more than one-third of annual anthropogenic GHG emissions are contributed by the food system [4,5]. The role of technology and the focus on food supply chains in supporting the efforts to reduce GHG emissions and achieve the SDGs have been previously highlighted in the literature [6]

and are receiving more attention in the recent management literature (e.g., [7–9]). In this paper, we present several pathways to achieve these impacts through food waste reduction, focusing on recent developments in artificial intelligence (AI).

It appears that, in spite of numerous recent studies on artificial intelligence (AI), there is still no commonly accepted definition of this concept [10]. The recent surge in AI was propelled by the ever-expanding internet, the Internet of Things (IoT), big data and analytics and other Industry 4.0 technologies [10]. The term intelligence is generally considered to be the ability of human beings to learn from experience by making appropriate sense of past and current observations and applying the knowledge appropriately to any new or unfamiliar situations. This kind of intelligence is becoming a reality for machines with the availability of large volumes of information across the internet, the ever-increasing production of information with existing IoT devices, and the ability to make sense of this data using sophisticated analytics tools. Machine learning and deep learning algorithms enable machines to learn, giving rise to the notion of machine intelligence, or artificial intelligence. The literature has recognized AI's potential to shape business practices and address societal challenges. For example, Loureiro et al. [11] have analyzed 404 research articles and categorized the past research into four clusters, including societal impact of AI, organizational impact of AI, AI systems and AI methodologies.

AI has found several innovative applications for food waste reduction (FWR) by helping to monitor quality, supporting smart inventory management, tracking waste levels in kitchens and reducing carbon footprints in industries [12–14]. Although several studies have examined AI for food waste reduction in hospitality and retail, few have explored how practitioners (i.e., food supply chain companies) themselves could use AI for FWR, despite the scale of the problem and the sustainability benefits of reducing it. We fill this research gap in this paper. It draws on two years of action research with industry partners across the agri-food supply chain in North-West Europe, carried out during the deployment of IoT sensors [15]. Working alongside these companies allowed us to identify specific situations in which AI could add value, from the perspective of practitioners rather than technology providers. We describe 13 such opportunities, discuss the barriers to realizing them and propose research objectives for future work.

The remainder of this paper is organized as follows. Section 2 is a literature review section. Section 3 discusses action research methodology and data collection. Section 4 discusses the results of our exploratory study, where several opportunities for FWR in food supply chains using AI. Section 5 discusses practical and theoretical contributions. Finally, Section 6 ends with conclusions and scope for future research.

2. Literature Review

We present our literature review in multiple sub-sections. We first present the literature on food waste and provide a context for the use of AI for FWR. We then review AI applications that support business performance and highlight the critical need for greater focus on FWR.

2.1. The Importance of Food Waste and Approaches to Reducing Food Waste

According to UNEP [1], the total quantity of food waste in the world was a staggering 1.05 billion tonnes in the year 2022, amounting to 19% of food available and in addition to the 13% of food lost in the supply chain (from post-harvest up to and excluding retail). It is believed that this value is more than one-third of global food production. The report further highlights that, on average, about 79 kg per capita of food is being wasted every year across the globe. In fact, food waste has not only serious economic impacts, but also more serious social and environmental impacts. If we saved wasted food and fed it to people, it could support the large population affected by hunger. The adverse environmental impacts of food

waste are even starker. The UNEP [1] states that if food waste were a country, it would be the third-largest source of greenhouse gas emissions. The level of food waste adds pressure to waste management systems and contributes to worsening climate change, nature and biodiversity loss and pollution and waste. Food waste has direct links with several SDGs, especially SDG 12 (Ensure sustainable consumption and production patterns) and SDG 13 (Action to combat climate change and its impacts). Recognizing the importance of food waste, the UN Sustainable Development Goal 12.3 aims to halve food waste and reduce food loss by 2030. Specifically, Target 12.3 says: "by 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses." Food waste is closely linked to climate action (SDG13) because methane from wasted food is a greenhouse gas more potent than carbon dioxide.

The importance of food and the challenges of managing the food system have been well documented [2,16]. Several countries across the world have agreed on the need to halve their food waste. The corresponding challenges are well recognized, and it has been agreed that a multi-pronged approach is needed to achieve this goal [17]. For example, several studies have looked at behavioral approaches (e.g., [18]) that will change household behavior in favor of creating less household waste. Others have examined policy approaches (e.g., [19]). For this paper, we use a technological approach similar to other studies in the literature (e.g., [20,21]). Specifically, we utilize our experiences in working with several European food companies for FWR by exploiting the latest developments in digital technologies [15], literature reviews [22], case studies [23], analyses (e.g., [24]) and other publications (e.g., [25]).

2.2. Artificial Intelligence and Its Business Applications

Based on several past references [26–28], Wamba-Taguimdje et al. [29] define artificial intelligence (AI) as "a set of 'theories and techniques used to create machines capable of simulating intelligence. AI is a general term that involves the use of a computer to model intelligent behavior with minimal human intervention'" (page 1894). According to these authors, the modern developments in AI have been propelled by the availability of a new generation of algorithms that have kept pace with the growing volumes of big data, the availability of computing power, and the availability of databases that can handle large volumes of data commensurate with the Big Data era. AI has been used in businesses in multiple ways. For example, Wamba-Taguimdje et al. [29] highlight that AI capabilities can support organizational performance. Enholm et al. [30] show that the appropriate enablers will not only improve AI use but can also generate additional first- and second-order effects that businesses should be aware of. Loureiro et al. [11] have identified dominant past and emerging themes in AI. Among the four AI topics they have categorized, the organizational impacts include work impacts (how work is transformed using AI), manufacturing, knowledge management systems, decision support systems and fuzzy logic/risk management systems. The authors highlight integrated Internet of Things sensors and AI as one of the four future trends. This area goes well with the theme of the current paper. AI can be used to support businesses in achieving SDGs. Di Vaio et al. [31] have presented a detailed literature review on linking AI with sustainable business models and achieving SDGs. Based on an extensive literature search, they highlight a research gap in the use of AI to support SDG 12 and urge future researchers to explore ways to use AI to support this SDG. The current paper aims to fill this research gap.

2.3. AI Studies for Food Waste Reduction

Over the past few years, there have been limited studies on how AI could be employed to reduce food waste in the food system and hence support sustainability. These studies are

summarized in Table 1. For example, Onyeaka et al. [32] have done a detailed literature review to understand how AI is being employed in the food sector for reducing food waste. They find that AI is beginning to be used in predicting food spoilage, for early detection of pathogens causing food decay, and for optimizing food storage and distribution. They also highlight key challenges impeding the applications of AI, including data quality issues, privacy and other legal issues, biases in AI models and legacy system compatibility.

Table 1. Studies that used AI for food waste reduction.

Reference	Main Topic	Methodology/ AI Topics	Examples of Impacts & Key Findings	Sustainability Outcome
Onyeaka et al. [32]	Literature review on new AI-based innovations to minimize food waste	Primarily predictive AI applications	Predicting food spoilage, early detection of pathogens, optimising distribution. Highlights challenges of data quality, AI bias and cost savings [33].	AI can reduce waste and support recycling
Nu et al. [12]	Assessing efficiency of an AI system in commercial kitchens (food production)	Descriptive and diagnostic AI applications	Food waste reduced by around 29% in three months by tracking inventory leftovers.	Upgrading the computer-vision version brings a further 30% reduction
Clark et al. [13]	Assessing performance of AI-driven food waste management in hospitality (food processing)	Primarily descriptive AI applications	Using scales, cameras and AI image recognition for expiration reminders and household integration.	Significant amount of food waste reduced, with environmental benefits
Anggraeni et al. [33]	Modelling household food waste drivers (households)	Predictive and prescriptive AI models	Bayesian networks and agent-based modelling to simulate household waste generation.	Consumer food waste level can be assessed to minimize retail food waste
Özekinci [34]	Causes of food waste and the role of AI	Primarily descriptive AI applications	Review of commercial AI tools for image recognition, freshness detection and compost separation.	Practical examples
Vukolić et al. [35]	Contribution of AI in FWR in hospitality (food processing)	Primarily descriptive AI applications	PLS-SEM modelling found significant links between AI integration and FWR in Serbian kitchens.	AI is used in menu planning and personalized service which reduces waste and improves efficiency.
Cejas [14]	Effectiveness of AI technologies for reducing food waste in restaurant operations (food redistribution)	Employs the Multiple-Stakeholder Target-Oriented Robust Optimization (MS-TORO) framework	The MS-TORO framework identified Too Good To Go as the most practical solution for its affordability and food redistribution model.	50% of restaurants experienced a significant drop in food waste
Agrawal et al. [36]	AI in food manufacturing to improve productivity and quality (food processing)	AI-driven transformation for sustainable efficiency	Discusses the barriers and enablers of AI-driven solutions for waste reduction. Suggests cross-sector collaboration.	Improves energy efficiency and lowers carbon footprints

Table 1. *Cont.*

Reference	Main Topic	Methodology/ AI Topics	Examples of Impacts & Key Findings	Sustainability Outcome
Seyam et al. [37]	Modelling food demand forecasting (supply chains)	Model is a preventive tool to avoid food waste.	Uses the predicted demand to replenish inventory	Avoiding waste by balancing supply with demand and avoiding inventory loss
Onyeaka et al. [38]	A literature review from circular economy perspective.	Potentials of AI to optimize food production and supply chains, redistribute excess food to those in need, and support circular economy initiatives.	Authors claim that AI can help reduce food waste in several ways. It helps to manage the corresponding risks too by improving transparency.	Circular economy perspective for waste reduction has been emphasized.
Nguyen et al. [39]	Special focus on using developments in nanotechnology with AI for food contamination and safety issues. Food supply chain focus.	A review of the advances in nano-enabled platforms for food safety.	Challenges of using nanotechnology with AI have been highlighted.	Food safety supports several SDGs.
Nguyen et al. [40]	Focus on the main advancements in AI-assisted design of antimicrobial nanomaterials for food safety (focusing on food supply chains)	Provides a literature review of AI-integrated antimicrobial nanomaterial systems.	The review highlights the challenges in data quality, toxicity prediction, reproducibility and more.	Food safety supports several SDGs.

Nu et al. [12] have discussed the effect of an AI-enabled food waste recording system on the amount of food wasted in commercial kitchens by collecting data with the help of a specific commercially available AI system. They find that, on average, AI-based touch-tracker systems help reduce food waste by 29% in three months without a corresponding decrease in sales. The AI system, involving touch sensors and usable data, helped to improve operational efficiency and reduce overproduction. Using a case study approach, Clark et al. [13] have reviewed AI-driven technology in the hospitality industry with a focus on food waste reduction. They examined how commercially available waste management systems helped reduce food waste. AI is being used in food supply chains to monitor quality and to maintain smart inventory, while AI's role in kitchen waste tracking, especially in commercial kitchens and restaurants, helps to reduce the carbon footprint [13,14].

Waste solution frameworks such as the MS-TORO framework [14] and other AI solutions such as Kitro, Winnow Vision and Leanpath have been shown to contribute to waste reduction through analytics, monitoring and predictive capabilities. The article [38] compares alternative AI solutions according to cost, feasibility, infrastructure requirements and waste-reduction effectiveness.

Agrawal et al. [36] discussed barriers and enablers of AI-driven solutions for waste reduction and suggested cross-sector collaboration. Modeling frameworks have also been discussed [37]. In line with the sustainability objectives of food supply chain companies, machine learning models and IoT streamline food production and optimize demand–supply and food redistribution, which in turn helps tackle food waste and advance the circular economy [38]. Nguyen et al. [39] used sustainable nano-sensors to enhance food safety as a preventive measure to avoid waste. The authors supported the use of nano-sensors for detecting contamination and spoilage early. A more recent article from Nguyen et al. [40]

has covered the role of AI and machine learning and how these can help enhance the design of antimicrobial nanomaterials, which in turn can help to preserve food from contamination.

While AI adoption and diffusion have a high impact in several industries, food manufacturers have yet to fully embrace AI to reduce waste. In general, AI applications to help reduce food waste result in net carbon benefits, as the carbon emissions saved through reduced food waste are much higher than the embedded carbon emissions from the technological infrastructure [41].

Thus, the literature shows evidence of the growing impact of AI tools in reducing food waste. Most AI-based food waste studies focus on the hospitality industry. However, there is equally good scope for using AI for FWR in other parts of food supply chains (e.g., food production and processing). The literature also shows that the list of AI applications for FWR is a growing field. Specifically, Di Vaio et al. [42] and Onyeaka et al. [32] highlight the need for more research on using AI to improve the agrifood sector. This paper aims to fill these important research gaps. It focuses on the potential of using AI for the UN SDGs, especially SDG12, by exploiting the synergy between IoT and AI and developing specific pathways for FWR in food supply chains. Using action research, this study identifies several specific situations where AI can contribute greatly to business practices on FWR in the food sector. The main research question is: "What are the opportunities for utilizing AI for FWR in food businesses that will help achieve SDGs?" Accordingly, our research objective is to explore ways in which AI can be used advantageously for FWR to achieve the SDGs.

3. Data and Methodology

Our data for this study have been derived via observations and interactions with EU food supply chains over a period of 2 years during the execution of a large international research project [15]. Details of the FSCs we used for data collection are included in Table 2 below. As the table highlights, the 13 companies come from multiple countries in North-West Europe. All of them belong to the food manufacturing, storage, or transportation sectors. These companies have been selected based on invitations sent to several companies and voluntary participation.

We had regular meetings with these companies over a period of more than 2 years and documented our observations, discussions and interactions via videos, photographs and minutes of the meetings [15]. We followed an Action Research approach [43,44] because of our extensive involvement in preliminary discussions, implementation, observation and data collection and analysis. Our action research involves bringing researchers (the academic experts) and practitioners (the FSC organizations) regularly together through intervention and transformation, dynamically learning more about the practitioner issues related to food waste and the potential use of solution approaches, including AI tools. Figure 1 illustrates the approach adopted to work with FSC organizations. Thus, we first had open discussions on food waste with food companies, identified their requirements, installed necessary hardware and software, collected data and analyzed the data to identify new opportunities for using AI. The number and frequency of meetings varied based on the participating companies' requirements, but we ensured company officials met the project team at least once a month to assess project progress. No proprietary data set was collected. Since our focus was understanding the newer opportunities offered by the IoT sensors, big data and AI, our data source was primarily based on the minutes of the meetings and email exchanges. The minutes and email exchanges are not shown in the paper due to confidentiality reasons but can be supplied to readers on request. These data sources are not large, and hence we did not resort to a thematic analysis or coding. We thoroughly analyzed these data sources to highlight the potential of AI for generating meaningful impacts in food supply chains. Several videos are available in the public domain (e.g., YouTube) [15].

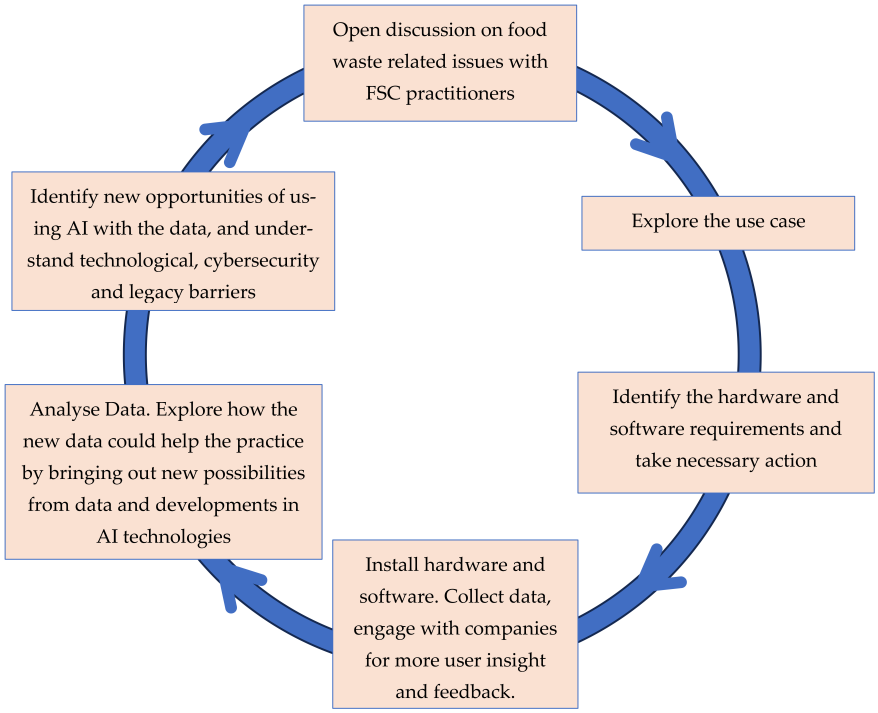


Figure 1. Research Approach.

Table 2. Food supply chain companies for data collection (Source: Ref. [15]).

	Stage of the Supply Chain	Country	Food Waste Issue
1.	Food processing in an Abattoir	UK	Meat waste due to non-uniform temperature distribution in dry ageing chambers (fridges)
2.	Food processing in an Abattoir	Republic of Ireland	Meat waste due to non-uniform temperature distribution in dry ageing chambers (fridges)
3.	Food storage in a frozen food company	UK	Food waste due to inadequate temperature in fridges
4.	Milk transportation	UK	Food waste due to inadequate temperature during transport
5.	Transport	UK	Food waste due to temperature anomalies during transport
6.	Transport	The Netherlands	Food waste due to inadequate volume of icepacks used during transport
7.	Storage and transport in multiple stages of the supply chain	Luxembourg	Food waste due to temperature abuse at the transport and storage stage of the supply chain
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.
9.	Storage	The Netherlands	Food waste due to pressure abuse at the storage stage of the supply chain
10.	Processing—Wine manufacturing	UK	Food waste of raw material when the right temperature and flow are not maintained in the production process.
11.	Production—raising cattle	UK	Food waste due to unacceptable quality of meat.
12.	Transportation	UK	Food waste in international transport.
13.	Food production, storage and transport	Germany	Food waste due to temperature anomalies during transport

4. Results—Opportunities for Waste Reduction in Food Supply Chains

In this section, we highlight only those interactions with food companies that shed light on opportunities to use artificial intelligence to solve specific problems in food supply

chains (Table 3). The opportunities below emerged during our repeated interactions via industry visits, regular project meetings with the companies, and were further discussed with academic partners in project meetings. As part of the larger project, we documented most interactions in meeting minutes or field-visit reports. These documents have been studied in detail to understand the multiple opportunities discussed in this section. The discussion here is intended to highlight new, exciting pathways in food supply chains with the emergence of tremendous data from IoT sensors and the promises of AI. A comprehensive discussion of each issue is beyond the scope of this paper due to space restrictions. Each of the pathways is briefly discussed in the following sub-sections.

Table 3. Opportunities for food supply chains in reducing food waste using AI.

Category	Activities and SDGs	Key Insights and AI Opportunities
Operations Capabilities of FSCs	Rapidly respond to customer complaints by diagnosing past errors. Primarily SDG 12 (Target 12.3) and SDG 13.	Enhance customer satisfaction. Develop AI models to detect anomalies in time-series data, diagnose self-defrosting fridgesand link complaints to sensor bottlenecks.
FSC Forecasting & Prediction	Utilize huge time-series data to understand and predict the future. Support routine industry queries.	Employ traditional SPC control charts and process capability on sensor data. Integrate IoT data with external weather/traffic data. Apply spectroscopy classification models.
Superior FSC Resilience & Performance	Develop prescriptive AI models generating insights for superior optimisation, addressing SDGs 1, 2, 3, 9, 12, 13.	Optimize last-mile icepacks, route optimisation for broken trucks, dynamic best-before dates, dry-ageing in abattoirs, cold chain route planning, rapid quality monitoringand self-healing refrigeration.

4.1. Enhance Operations Capabilities of FSCs by Developing New Diagnostic Tools

Some of our interactions with food supply chains have given us interesting insights into developing new diagnostic capabilities.

4.1.1. Opportunity 1: Anomaly Detection

Real-time sensor data are mostly shown in raw form, and it is usually difficult to quickly identify anomalies. To handle this raw data and enable effective anomaly detection, data processing and machine learning are essential to reveal important patterns and highlight unusual behavior. Studies do exist in the literature about how IoT sensor data can be used to quickly detect the presence of unusual states within the system (e.g., [45,46]), but it is well recognized that such anomaly detection algorithms often need to be tailored to specific applications. In food supply chains, IoT sensors are used not only to sense a parameter but also to generate automatic alerts if the parameter deviates significantly from preset thresholds [25]. For example, the parameter could be temperature if we consider the application of maintaining food at an optimal temperature. Threshold values of temperature can be specified for a given application. For example, for storing chilled food, the temperature thresholds could be 5 °C (lower threshold) and 8 °C (upper threshold). Ideally, the food should be stored below the lower threshold to guarantee its quality.

However, a significant quality deterioration is expected if the temperature goes above the upper threshold. Thus, exceeding the upper threshold indicates more severe deterioration in the quality of the stored food. In our preliminary study, we found that a suitable rectified linear transformation of sensor data using preset threshold values can help amplify deviations and help locate them quite quickly. However, more effort towards such newer AI models is necessary not only to locate any deviation from optimal temperature thresholds,

but also to help forecast the future occurrence of similar deviations. These newer models should clearly adhere to all requirements for food quality, safety and legal compliance. For example, the temperature thresholds used above (5 °C and 8 °C) are not universally accepted thresholds for all food categories. In addition to temperature, other factors such as humidity must be considered. These parameters can also vary depending on storage conditions. All these parameters should be considered while developing new AI models.

4.1.2. Opportunity 2: Diagnosing When a Fridge Enters Self-Defrosting Mode

An interesting issue that came up during our work with food businesses is that fridges and freezers used to store food items seem to show unusual patterns during their defrosting cycles. Most frost-free fridges are equipped with automatic defrosting mechanisms to prevent ice buildup. However, some food businesses report that the storage temperature may not be optimal during defrosting cycles. Prior to the installation of IoT sensors in their fridges, most businesses had to manually estimate when a fridge would enter its defrosting cycle. However, with the availability of continuous sensors, it is now possible to (i) predict the likelihood of a defrosting cycle occurring in the next few hours, and (ii) understand the temperature fluctuations inside the fridge during the defrosting periods. For this diagnosis, sophisticated AI models are required that identify patterns in the variations of temperatures (after, of course, accounting for the periods when the fridge is manually opened and closed for loading and unloading), identify the patterns related to defrosting cycles, and then use the learning to predict the chance of the fridge entering defrosting mode within a pre-specified timeframe. The model could automatically send alerts to food owners if it predicts a fridge is likely to enter defrosting mode, say, in the next day, so the company can move the food to another fridge. Understanding temperature variations in the fridge during defrosting mode can further help in estimating the loss of food quality in case a food item was continuously kept in the fridge during a defrosting cycle.

4.1.3. Opportunity 3: Linking Customer Complaints to Sensor Data and Identifying Bottlenecks

When customers report receiving products in suboptimal condition, studying sensor data and using intelligent transportation AI models [47] can diagnose the cause and identify where and why the deviation occurred. The starting point is the identification of the truck used to deliver goods to the specific customer. Then, the specific journey (date and precise time) that made the delivery of the product in question to the complaining customer should be identified. The sensor data for this trip should then be studied in detail to identify any unusual anomalies compared to similar trips made by this truck or another truck on the same route on the same day or in the previous or subsequent one or two days. One or more sensor parameters need to be tracked in this way depending on the nature of the complaint. For example, if the complaint is about eggs being delivered broken, then the right parameter to study would be the accelerometer data used to identify unusual vibrations. Careful data analysis should pinpoint the truck's location (e.g., the specific road) when a malfunction begins (for example, excessive vibration due to potholes). Precisely locating such trouble points requires sophisticated AI and machine-learning algorithms. AI is further needed to decide on a suitable course of action for future trips. Road pothole data (sensed by accelerometers) should be used to suggest the optimal routes to follow considering real-time temperature and vibration data. Real-time traffic data (or a sophisticated forecast using past traffic-jam data) would be a good opportunity to use AI to suggest the best routes for delivery trucks [25] and, more importantly, the roads to avoid to minimize customer complaints. A machine-learning/AI model around customer complaints will be very useful,

but further AI-based proactive analyses to prevent future customer complaints will be even more useful.

4.2. FSC Forecasting and Prediction Through Predictive Tools to Help Achieve FWR

In this section, we provide examples from our interactions with food supply chains on how new predictive models can be used for forecasting and prediction.

4.2.1. Opportunity 4: Quality Management and Statistical Process Control

From a research point of view, there are opportunities to utilize some topics on quality management to study the time-series data. Statistical process control (SPC) is a technique, based on statistical methods and tools, to control, monitor, analyze and improve the quality of a process [48,49]. To do so, a series of observations is made, and time-series data are collected. In the context of IoT sensors for tracking food quality, the sensors keep sending such time-series data on temperature and other food quality characteristics. Thus, the data from IoT sensors can be considered a measure to study whether the temperature control mechanisms in the fridges or freezers are in control and provide the required cooling. Thus, there is close similarity between the purpose of statistical process control and the requirement to maintain food parameters at optimal levels for reducing food waste. If the temperature control mechanism in the fridge is not in control, it will show random variations and may cause the temperature (or any other relevant parameter) to rise continuously. One of the prime requirements of maintaining food quality is to make sure that the food is maintained at optimal levels. Thus, statistical process control ideas can be borrowed to study the behavior of temperature and other IoT sensor data. Some of the well-known principles and methods used in SPC can thus be employed to study the behavior of IoT data. Specifically, we can use X-bar and R-charts to check whether there are any undue variations in the data. We use the previous behavior of the parameter to set the control chart limits. Further, we could use the idea of process capability analysis to check whether the cooling process in the fridge or freezer is under control. Control charts and process capability analysis can be used to send warning signals to food owners when the food parameters might start to go out of control, allowing them to take corrective actions immediately. The ultimate result is thus to save the food from becoming waste. As a scientific method based on statistical averaging, SPC findings are likely to be reliable and are unlikely to cause false alarms. However, these methods do not completely eliminate false alarms. Newer AI models that draw on the foundations laid by SPC are required for quality management and control.

4.2.2. Opportunity 5: Combine IoT Data with External Data for Better Prediction

Advanced food systems are increasingly leveraging predictive AI models, most commonly to estimate product quality, optimize logistics and predict product temperature. However, a recent systematic review of AI applications in food cold chains found no studies combining physical sensor recordings with external data sources such as weather forecasts or live traffic feeds and identified this integration as a promising direction [50]. Because weather and traffic data are widely available through application programming interfaces (APIs), there is an opportunity to fuse them with real-time sensor data to support decisions during transport. For example, by combining external temperature forecasts with historical transportation temperature data, a regression model can be used to predict the maximum safe delivery distance or duration for perishable goods like human milk. This allows logistics providers to make data-driven routing and packaging decisions that account for environmental conditions, ultimately reducing spoilage risk and improving delivery planning. Similarly, external data integration can be used to identify traffic bottlenecks

or infrastructure gaps that consistently contribute to temperature deviations during transport. In such cases, newer AI models can recommend pre-emptive actions such as route adjustments or collaboration with local authorities to mitigate recurring risks.

4.2.3. Opportunity 6: Spectroscopy-Based Classification Models for On-Site Quality Estimation

Miniaturized spectroscopy devices present a promising platform for on-the-spot quality estimation in various stages of the food supply chain [51]. Advances in machine learning now make it feasible to build classification models that interpret spectral data to assess product freshness or contamination levels. When deployed on portable spectrometers, these models enable rapid, non-invasive evaluation of food quality without the need for laboratory equipment. For example, such tools can be used to classify milk samples into freshness categories based on chemical signatures indicative of spoilage [52]. The classification output can then support real-time decisions, such as whether to accept, reject, or prioritize certain batches for immediate delivery. Both the miniaturized spectroscopy devices and the AI-based quality assessment models need further research to realize AI's potential.

4.3. Achieve Superior FSC Performance Through Prescriptive Tools

In this section, we provide some examples based on our interactions with food supply chains on how new prescriptive models can be used for FSC optimization.

4.3.1. Opportunity 7: Use AI to Prescribe the Number of Icepacks for a Given Frozen Delivery

In last-mile food delivery, vans are often divided into multiple compartments, each catering to different cooling requirements. Determining the optimal number of icepacks for each box is crucial for maintaining product integrity while optimizing operational costs. New prescriptive AI models are required to automate this decision by factoring in real-time variables such as (i) real-time weather conditions, (ii) real-time traffic conditions, (iii) conditions of the road surfaces for a given route, and (iv) the specific temperature requirements of the transported products. While the use of icepacks in temperature-controlled delivery is quite common, there is very little literature (e.g., [53]) aimed at the study of icepacks in frozen distribution.

4.3.2. Opportunity 8: Route Optimization

Another interesting potential use of AI is providing decision support in cases where food travels in a truck, and the IoT data show that the food is not being kept at the right parameters. This could possibly be because the temperature control mechanism in the truck has failed. Dedicated AI algorithms could send out alerts to the corresponding food owner and to the driver of the truck. In case the issue cannot be resolved immediately, it might not be a good idea to continue the journey of the truck, as the food may have become waste by the time the truck reaches the intended destination. In these cases, newer AI models could be developed to help sell the food at a nearby demand point rather than continuing the original journey. In such cases, a decision-support tool is required to do multiple activities (which can provide rich opportunities for the use of prescriptive AI):

- To locate the nearest food demand points (e.g., local grocery stores or food banks) where food can be diverted to ensure that it will be used before becoming waste. Existing databases such as Google's can be used to locate the nearest demand points;
- To identify the shortest route from the truck's current location to these demand points, given road-network constraints and real-time traffic data. The shortest route can be

identified using established network algorithms, while the real-time traffic data can be obtained from existing databases (such as Android);

- To provide support in terms of the best price for the food to help enter into negotiations with the demand point. Re-estimating the best-before date using mathematical models that consider the loss of food quality due to the exposure to adverse conditions can help indicate a reasonable price to negotiate with the demand points.

4.3.3. Opportunity 9: Dynamic Due Date

Newer sophisticated AI-based analyses of IoT sensor data can help detect any sub-optimal storage conditions of the stored food and, depending on the length of exposure to sub-optimal conditions, can estimate the chances of food quality loss. As a result, it is possible to predict the "best-before-date" for the food on a dynamic basis. Though there is some limited previous literature (before the AI era) that attempted a similar analysis using RFID and sensor data (e.g., [54]), there are not many recent studies in this context since the resurgence of AI. Using a function that defines the dynamic due date as the original due date minus the impact of adverse storage conditions, machine learning algorithms such as artificial neural networks can continuously revise the best before date [55,56]. External data such as weather data can also be incorporated into the model. Accordingly, newer complex AI models can be developed to estimate the life of the food and set the dynamic due date by which the food has to be consumed before it is likely to become waste.

4.3.4. Opportunity 10: Optimizing Dry Aging in Abattoirs

The dry-aging process in abattoirs is critical in enhancing the flavor, tenderness and overall quality of beef. However, despite its importance, the dry-aging process often lacks optimization, leading to inefficiencies and unnecessary product losses [57]. Temperature and humidity must be carefully balanced to maintain meat quality and yield. Despite the long history of dry-aging, optimal conditions remain elusive due to the interplay of numerous variables: (i) weight and size of individual hindquarters; (ii) arrangement of cuts within the chamber; and (iii) proximity of refrigeration units or airflow sources. Newer prescriptive AI models hold promise, but, to our knowledge, there are still very few studies in this direction.

4.3.5. Opportunity 11: Cold Chain Route Planning

One critical challenge in transporting temperature-sensitive materials, such as human donor milk, is ensuring storage temperatures remain within safe limits throughout the journey. For donor services, this uncertainty poses significant risks, as exceeding the temperature storage limits could compromise the integrity of the transported materials, leading to waste of high-value materials and potentially critical shortages. Because the materials in transport cannot be easily replenished, organizations distributing human milk tend to adopt conservative approaches and fulfill jobs only within a shorter commuting distance to minimize risk. This is especially true because it is unknown how extreme heat, as may be experienced in summer months, affects the cooling profile and the reliability of maintaining the required −10 °C temperature in medical bags. AI and machine learning (ML) offer a promising solution to address this challenge. ML can be utilized to estimate the maximum safe transport distance based on a set of dynamic parameters. By integrating additional features or 'labels' into the time-series temperature dataset—such as current outdoor temperature, vehicle type, bag size, milk quantity, and total journey duration—meaningful insights can be extracted for accurate distance and time predictions. In our preliminary work, we compared four regression models (linear regression, decision tree, neural network and Random Forest) for predicting the rise in bag temperature from journey

time, outdoor temperature, quantity of milk, bag size and mode of transport. The models were trained on 766 sensor readings from 117 journeys. Because readings from the same journey are not independent, they were evaluated with journey-grouped cross-validation (5 repeats), in which all readings from a journey were held out together and were compared with a baseline that always predicts the mean rise. The Random Forest performed best on unseen journeys, with an RMSE of 0.82 °C, an MAE of 0.47 °C and an R^2 of 0.37, compared with an RMSE of 1.05 °C for the baseline. Random Forests combine the outputs of many decision trees to improve accuracy and reduce overfitting, and their variable importance measures allowed us to explain the predictions to the milk bank, ensuring transparency and building trust in the model's recommendations. By using journey-specific parameters combined with the starting temperature recorded by onboard sensors, the model has shown promise in predicting the time it takes for the temperature inside the transport bag to reach the critical threshold of −10 °C. With the maximum delivery time calculated, maximum distance can also be inferred using an estimated average driving speed.

These results are preliminary. The dataset was small, with few long journeys or journeys in hot weather, and the model tended to underpredict large temperature rises. Further details of the model are beyond the scope of this exploratory study, but this is an area for future research, and more sophisticated AI models trained on larger datasets are needed to support food businesses. As highlighted in Section 4.1.1, the threshold value used in the preliminary model (−10 °C) was suggested by the food supply chain partner, but newer AI models should consider appropriate threshold values for different food categories and storage conditions.

4.3.6. Opportunity 12: Rapid Food Quality Monitoring

Historically, quantifiable measurements of food freshness would have only been possible via laboratory analysis. However, machine learning (ML) techniques combined with spectral data present a promising solution to bring quantifiable spoilage metrics directly to consumers [58]. By combining spectroscopy with advanced ML algorithms, it is possible to perform rapid, reliable assessments of food quality, providing objective data to replace or complement expiration dates. In the case of food supply chains, our preliminary effort was implemented using the handheld FreshDetect BFD-100 Fluorescence Spectrometer, although the approach can be generalized to any spectrometer. Handheld devices like this empower end-users to perform their own food quality assessments, enabling informed decisions about product freshness. The FreshDetect device had previously been employed for evaluating meat products, such as chicken and pork [59]. However, in our preliminary study, we developed a new model specifically for the on-the-fly assessment of cow's milk [52]. Spectra of milk samples were collected with the spectrometer, where we identified that the spectrometer's 'peak' represented riboflavin (Vitamin B2). Since riboflavin decreases as milk acidity increases, we collected pH data using a pH meter to monitor acidity during our experimentation. This enabled the creation of a classification model to determine whether milk was safe to consume or spoiled, using a pH threshold of 6.5.

Balancing sensitivity and specificity is crucial in this application. Sensitivity reflects the model's ability to correctly identify spoiled milk, an essential metric in scenarios where missing cases of spoilage could lead to significant consequences, such as health risks, regulatory issues and economic losses. Specificity, on the other hand, measures the model's accuracy in identifying fresh milk. While specificity is less critical, overly cautious predictions that misclassify fresh milk as spoiled can lead to unnecessary waste and consumer dissatisfaction. In this context, prioritizing sensitivity is vital to ensure consumer safety and maintain product quality. However, reducing false positives for fresh milk is equally

important to minimize waste and achieve a balance between the two. This trade-off poses a key challenge in developing machine learning models for food quality monitoring.

In our preliminary study [52], seven classification algorithms were trained on 3756 spectra recorded over 48 h. A naïve Bayes classifier performed best on an independent hold-out set, with an accuracy of 95.4%. The neural network and ensemble models achieved slightly higher sensitivity (96.9–97.9%), but their specificity was only 72.5%. Naïve Bayes balanced the two better, with a sensitivity of 96.4% and a specificity of 88.2%, so it was selected as the preferred model. These results come from a small proof-of-principle dataset, in which pH was measured on a reference sample and elapsed time was used as a proxy for acidity. They should therefore be treated as indicative until the model is validated on larger and more varied milk samples. We are confident that newer AI models will build on this effort and support rapid food quality monitoring for milk and other food products. As highlighted in Section 4.1.1, the threshold pH value of 6.5 used in the preliminary study was suggested by the food supply chain partner, but newer AI models should consider appropriate threshold values for different food categories and storage conditions for all relevant parameters.

4.3.7. Opportunity 13: Develop AI-Embedded Self-Healing Refrigeration Systems

Looking ahead, we envision a future where AI-enabled control systems are fully integrated with sensor networks in cold storage infrastructure—both in warehouses and vehicles. With the increasing integration of IoT sensors in business processes, we can envisage that future temperature control mechanisms in fridges, whether in warehouses or in transit, could become a "self-healing" system, where prescriptive AI autonomously detects faults and adjusts settings in real time to maintain optimal conditions. This convergence of control and sensing represents the next frontier in smart, resilient food supply chains.

5. Discussion—Practical and Theoretical Contributions of the Paper

The opportunities described in detail in the previous section make interesting practical contributions. They provide new ways of reducing food waste in food supply chain companies using the evolving field of artificial intelligence. While supporting food waste reduction, as highlighted in Table 3, they help respond to customer complaints rapidly and thus help enhance customer satisfaction. They can help in generating solutions for routine industry queries, as the time series data from sensors is a valuable record of historical data. All the opportunities are expected to help in achieving primarily SDG 12 and SDG 13, but also help in achieving other secondary SDGs, including no poverty (SDG 1), zero hunger (SDG 2), good health and well-being (SDG 3), and industry, innovation and infrastructure (SDG 9). When newer AI models are developed in the future, these SDGs can be explicitly linked.

While the 13 opportunities provide exciting avenues for the use of AI for FWR, it is important to recognize the technological issues and barriers for such a development. Sensor technology is evolving rapidly with increasing power and reducing size. Sometimes new technology is not compatible with existing systems, which requires legacy issues to be managed appropriately. New generations of sensors bring new challenges in sensor calibration and reliability [32]. Due to technological limitations, sensor outputs can have missing or inconsistent data, requiring appropriate calibration mechanisms. Cybersecurity aspects should be considered [60]. Thus, continued development of AI for FWR requires appropriate considerations of technology, cybersecurity and legacy barriers.

The results in Section 4 have significant theoretical and research implications too. Exciting new opportunities for research emerge with the increasing availability of historical data and evolving power of AI. The new research opportunities discussed so far in this section are summarized as important research objectives in Figure 2 to help future researchers. Thus, AI offers not only new and exciting practical applications in the food industry but

also new avenues for theoretical exploration. Existing and new theories can explain the exploitation of the 13 opportunities presented in Section 4 and help study organizational capabilities, technology-enabled decision-making and sustainable supply chain management in the context of AI for FWR. For example, the resource-based view can explain [60] how gaining inimitable knowledge by repeatedly using innovative AI applications will provide a competitive edge to food companies. The rapidly evolving AI landscape can also serve as a strong context for testing the dynamic capability view. The inconsistencies between rapid technology advancement and not-so-rapid adoption by industry can be examined via paradox theory. Please note that these objectives are indicative and reflect the current state of the art but will certainly evolve in the future.

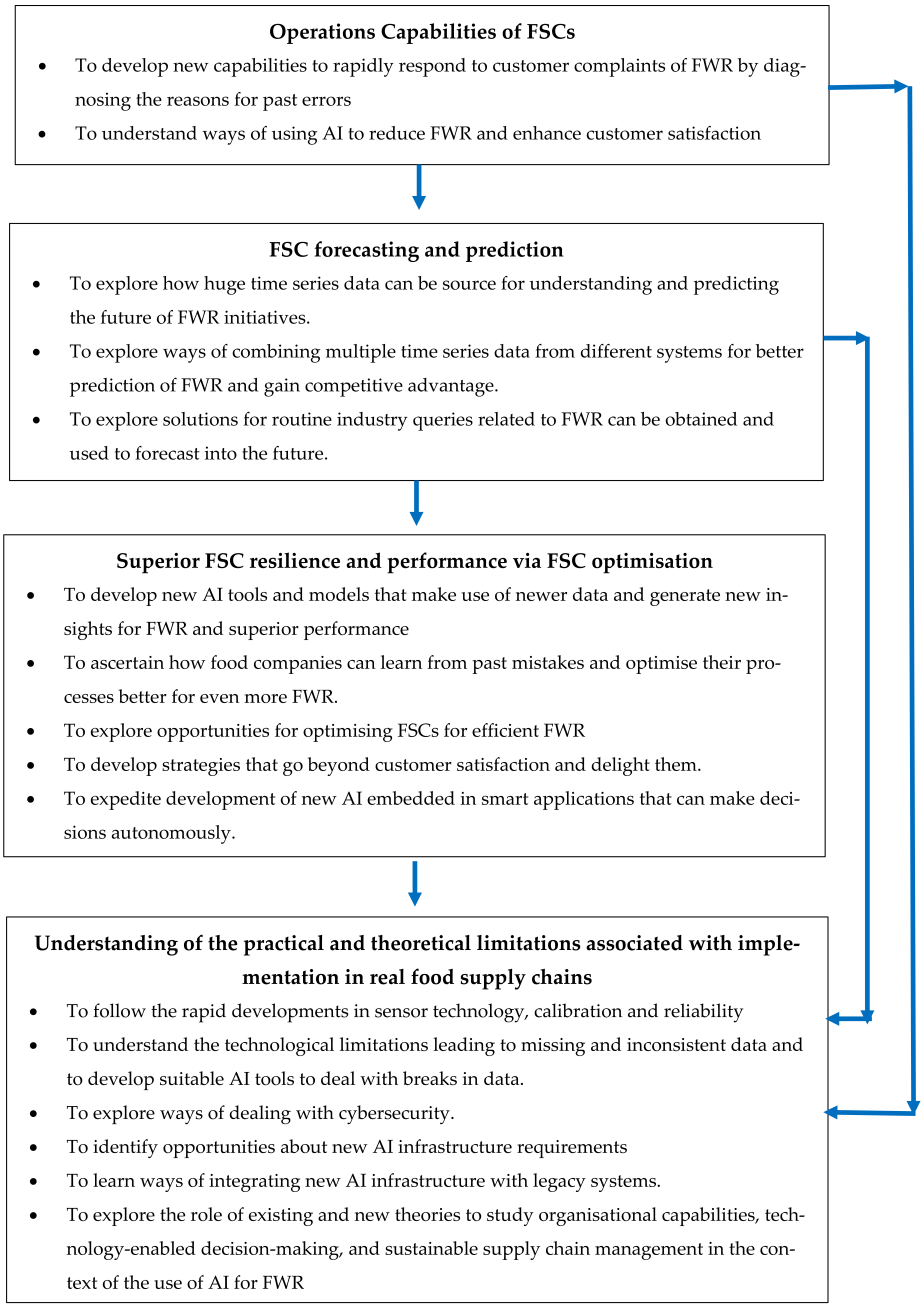


Figure 2. Research Objectives on the use of AI for FWR for future researchers for achieving SDGs (Arrows indicate generally increasing levels of complexity in terms of analytical sophistication, organizational capability, decision autonomy, data integration, value creation and/or technological complexity).

6. Conclusions

Using exploratory action research, this study has identified new opportunities for reducing food waste in food supply chains using the growing power of artificial intelligence. These opportunities are classified in terms of enhancing the operational capabilities of food supply chains, better forecasting and prediction and improving resilience and performance. A series of research objectives has been developed to support future researchers. These new opportunities are very useful in practice for improving the resilience of food supply chains and for reducing food waste. These practical implications have been discussed in the previous section.

Despite identifying exciting new opportunities for using AI to reduce food waste, this study is not without limitations. As mentioned earlier, this study is based on a large-scale European project, and hence the choice of companies and the consequent interactions are limited to the scope offered by the project. For example, only food companies in North-West European countries where the project was active could be approached. Other countries could not be targeted. We sent invitations to all food companies across these countries, but our sample was limited to those that voluntarily came forward to work with us. Further, the opportunities identified were based on the practical requirements brought forward by the companies during our interactions. Future studies can establish the applicability of various new AI applications across different food supply chain contexts (more countries and more food products). The findings of this study may have been influenced by the methodology of action research. Although sufficient care was taken to eliminate researcher bias, future studies can use other methodologies, such as qualitative, case study, or quantitative approaches, to extend these findings.

Despite these limitations, this study has provided useful research objectives that could be taken up by future researchers. It is hoped that the opportunities identified in this study will provide a strong basis for new and more exciting future research on using AI to reduce food waste across the globe.

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