Review

Applying Artificial Intelligence to Promote Sustainability

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Abstract: This study reviews the application of artificial intelligence (AI) throughout the food value chain and how it can be leveraged to help companies become more sustainable. A literature review across different parts of the food value chain was conducted to provide an overview of the main themes of current and future AI applications throughout the food industry. Moreover, the paper focuses on the benefits and challenges of change management when integrating AI. A documentary Systematic Review using PRISMA research was conducted to find and analyze the aforementioned applications. The key insight is that change progress varies significantly. Today’s applications are primarily found within food inspection and quality assurance due to relatively straightforward AI applications in the value chain. Such technology is mainly image-based. Companies can use the interconnectedness of AI and sustainability by becoming more efficient through AI and simultaneously saving emissions and resources through optimizing processes.

Keywords: sustainability; artificial intelligence; change management; food industry; value chain; literature review

1. Introduction

With a rising world population expected to reach over 9 billion by 2050, there comes an anticipated increase of 50% in food demand from 2012 to 2050 [1]. This is a sizeable challenge for the food industry (FI), especially considering climate change, pandemics, war, and limited availability of resources [2]. The FI is also highly competitive and evolving, while consumers are raising their demands across characteristics such as food quality, safety, diversity, and sustainability [3]. Since the FI is also the most intense human resource among all manufacturing industries, especially within food production and packaging, supply is constrained to human performance, and food safety is subject to human errors [4]. To face these obstacles, the FI must evolve considerably, which also entails adopting more sustainable practices and drastically reducing food waste.

The purpose of this paper is to review the literature on the application of artificial intelligence (AI) in the FI. Going into depth within this subject area is highly relevant, as it can help guide the way forward for companies and provide them with a sense of direction. This paper contributes to the literature by providing a detailed view of the literature regarding AI within the FI. This is especially useful due to the speed of developments [5], which necessitates constant updates to available applications and adopted practices. Additionally, this paper aims to further unite the concept of sustainability with the existing literature on AI in the FI by taking on a holistic view where different stakeholders are considered and where sustainability is an integral part from the beginning when considerations around AI are made [6]. This review also provides insight into the challenges and drawbacks of using AI in the FI. The emerging fear of being replaced by robots [7] or the assumption that progress inherently leads to more sustainable practices [8] are examples of why all arguments must be listed and assessed to prevent the discourse around AI from being dominated by incomplete understanding or misconceptions.
Given the challenges that the FI is facing, there is pressure on the FI to innovate and explore new solutions [9]. AI, machine learning (ML), blockchain technology (BCT), and other innovations are therefore deployed to enhance the entire food value chain (FVC) [4] and, as a result, minimize human error, waste, and packaging cost while improving speed and personalization [10]. The expected benefits are huge: AI analytics are estimated to add global economic activity of approximately USD 13 trillion by 2030, corresponding to an additional 1.2% annual global GDP, especially regarding supply chain-related operations [11]. Meanwhile, AI integration within the food and beverage industry is expected to reach a market value of USD 29.94 billion by 2026 at a CAGR (compound annual growth rate) of 45.8%, and BCT within the agri-food industry is projected to reach another USD 948 million by 2025, at an even higher CAGR of 48.1% [12,13]. Consequently, integrating these new technologies with the necessary understanding and competencies is the foundation that enables companies to digitally transform [14], and this is also essential to the FI.

As a result, there has been a rise in the degree of digitalization in the food industry [15] and a sharp increase in the number of publications and citations related to the fourth industrial revolution in the FI [3]. Especially within the most recent years, there has been a significant surge, with the number of publications on AI applications in the agri-food industry more than doubling from 2019 to 2020, which indicates the speed in new findings and applications [5].

However, throughout these developments, the concept and integration of sustainability are still in their early stages. For example, Di Vaio et al. [16] found that there is still very little research mentioning concepts like “environmentally aware” and “stakeholders” in combination with AI and the FI. This is the case even though AI might negatively impact sustainability matters such as data protection or social equity [16] if no further action is taken. AI systems often require large amounts of data to function effectively, including personal information about consumers’ buying habits, dietary preferences, and health information. Ethical use of this data involves ensuring that data are collected, stored, and processed strictly following privacy laws and standards and that consumers are informed about what data are collected and how they will be used. AI systems can inadvertently perpetuate or even exacerbate biases if trained on skewed or non-representative data sets. In the food industry, this could manifest in algorithms that target or exclude certain demographics in marketing campaigns or product recommendations. Fairness involves careful oversight of data collection, algorithm training, and ongoing monitoring to detect and correct biases. Conversely, AI and other technologies can significantly accelerate the adoption of more sustainable practices in the FI if integrated from the beginning and handled with care [17], because improved efficiency and reduced costs typically lead to more productive use of materials and lower resource consumption. It is an example of how a company’s triple bottom line [18] can be affected, as reducing emissions, waste, and energy usage could materialize through AI contributing to sustainability initiatives. At the same time, a decrease in health and safety incidents could positively affect society, next to the more apparent benefits concerning the increase in profits gained through optimizing processes.

As mentioned, combining the three areas of AI, FI, and sustainability remains rare, and very few literature studies exist on it. The role of AI within sustainability and thus also within the FI is especially under-researched [6], even though companies can contribute and have increasing aspirations to use AI for these purposes [19]. It is also highly relevant for policymakers to consider how to best handle these emerging topics [6]. Even more so, a holistic approach is critical to ensure knowledge sharing, cooperation, and collaboration between stakeholders [16,20], which, in turn, is necessary to establish the safe and sustainable use of AI. As Figure 1 exemplifies, there are numerous ways that AI can optimize the entire FVC. Efficiency is thereby increased, simultaneously improving the FVC’s sustainability by saving resources, ensuring food safety and animal welfare, and much more.
Most studies discuss a specific technology or application or focus on a particular part of the FVC. While they are useful in providing in-depth takeaways for the relevant audience, their technicality, as well as their specificity, can also seem overwhelming to companies and their employees, who still need to become acquainted with the vocabulary and concepts [22]. The nature of the publications, which are usually from a technological or science perspective but rarely from a business perspective, makes it especially difficult for business leaders to make relevant decisions and adjust their strategies accordingly. This is why this paper focuses on a comprehensive review of the entire food value chain to provide a holistic understanding and overview (Figure 2 presents core functions of production, processing, and distribution in the value chain).

Figure 1. Sustainable food value chain leveraging AI. Source: [3]. Source: [21].

Figure 2. Food value chain overview. Source: own illustration following FAO, 2014.

2. Materials and Methods

2.1. Type of Study

This section delineates the methodology utilized in executing an extensive literature review on applying artificial intelligence (AI) within the food value chain (FVC) and its potential to enhance corporate sustainability. The review synthesizes existing research findings to discern patterns, themes, and gaps in the literature, thereby establishing a basis for future research. A systematic approach, namely the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, was employed to ensure rigorous and comprehensive analysis.
Since the technology around AI and related terms such as big data or ML is continuously evolving and still in its relatively early stages [23], some uncertainty remains around the vocabulary used and hence, how to search the literature. This applies to the meaning of the terms and the context in which they are used due to the range of perspectives available. However, they can be linked to parts of the process chain, i.e., data collection, data storage and transferring data analysis, and data visualization [22]. As no universally recognized definition of AI and its related vocabulary exists, the various terms will be explained below in the manner in which they have been commonly used throughout the existing literature. However, a simplified overview of the key terms could be the following: big data is used for data acquisition, blockchain is used for data security, and AI is used for data processing [22].

1. First coined by Kevin Ashton in 1999, IoT is a technology paradigm contemplated as a network of digitally connected devices and machines. Here, the digital connection of devices, systems, and humans occurs over the Internet. The term refers to the network of physical objects—“things”—that can be embedded with sensors, software, and other technologies to connect and exchange data with other devices and systems over the Internet. IoT has grown rapidly in recent years due to the decline in the cost of connected sensors and the increase in Internet accessibility. It will continue to affect various sectors, such as home automation, healthcare, agriculture, and industrial automation.

2. Big data typically involves collecting large and complex data sets and originates from different sources [24]. Next to the characteristics of high volume and variety in data format, it is also known for its velocity. That is, it is close to real-time collection speed [22]. The amount of data requires significant storage and sophisticated technology to process and gain insights. Two of the main concerns that go hand-in-hand with big data revolve around data security and privacy. Much of the growth in big data is driven by increased data capture across various devices and platforms, including social media interactions, e-commerce transactions, sensors embedded in devices (part of the Internet of Things), and mobile devices. The concept of big data has been evolving with the advancement of technology. As storage capacities have grown and computational power has increased, they can handle vast amounts of data quickly and relatively inexpensively.

3. Regarding data storage, cloud computing and its related extensions offer an alternative to local data storage. It has also become particularly relevant with the rise of big data that require management [22]. Users can store and access data remotely through a network of remote servers, typically offered as a service by different providers. Cloud computing has five technical characteristics: large-scale computing resources, high scalability and elastic shared resource pool, dynamic resource scheduling, and general purpose [25]. Its benefits include increased reliability, security, flexibility, and accessibility.

4. The field of AI is understood to be mimicking human intelligence [26]. Therefore, the other concepts below, like ML and deep learning, are also considered to be included when talking about AI. A subsection of AI is rule-based AI, which, as the name indicates, runs based on pre-defined rules, usually in the form of if–then statements. It is a comparatively simpler form of AI than the ones below and can only handle limited complexity.

5. ML is a subfield of AI based on the idea that computer systems are taught to recognize patterns and make predictions and decisions through various methods and algorithms using data to fit models [3]. Traditionally, these systems were programmed to conduct a specific task; however, with ML, the approach is to train them more broadly, which offers benefits including increased automation, accuracy, and adaptability. ML focuses on building systems that learn from and make data-based decisions. Unlike traditional programming, where humans explicitly code all the rules, machine learning algorithms use statistical techniques to learn patterns in data and make predictions or
decisions without being explicitly programmed to perform the task. ML has evolved from pattern recognition and the theory that computers can learn without being programmed to perform specific tasks. It powers recommendation systems on platforms like Netflix and Amazon, tailoring content to individual user preferences. It is used extensively in services like Google Photos and voice-activated assistants like Siri and Alexa. ML can also be used to predict diseases from various medical data and personalize treatment. In finance, e.g., it is used for credit scoring, algorithmic trading, and risk management.

6. DL (deep learning), in return, is a subset of ML and consequently a narrower approach. The main differences between ML and DL lie in the data type and size they can process and the complexity of the various models. ML typically has a simpler, one-layer structure. At the same time, DL can process multiple layers simultaneously [22] and is thus able to solve more complex problems and be used in image and speech recognition. DL has revolutionized many fields of machine learning through its ability to process large volumes of data and automatically discover the representations needed for detection or classification. DL has become a foundational technology for many modern AI applications, offering substantial improvements over previous techniques in terms of performance and flexibility. Deep learning excels in image recognition, object detection, and video analysis. This capability is used in applications from automated surveillance systems to medical diagnostic tools. DL applied techniques like recurrent neural networks (RNNs) and transformers have improved the ability of machines to understand and generate human language, powering systems like chatbots and translation services. It has powered the language understanding and speech recognition capabilities of virtual assistants like Siri, Alexa, and Google Assistant. DL’s development is closely tied to broader AI and machine learning trends, shaping the future of how intelligent systems are designed and implemented.

7. Blockchain is a database or ledger that records and stores data blocks and operates decentrally. When adding a new block containing data to the chain, it is equipped with a timestamp and a hash, i.e., a cryptographic “fingerprint” [8], which is linked to the hash of the previous block and is almost instantaneously shared with the entire network. The blocks cannot be modified unless consent is given by the network, thus rendering the chain tamper-proof. The technology has gained much attention, particularly for its immutable and more transparent, secure, and permanent abilities compared to previously existing methods. Based on what it is combined with, it can be helpful in a wide range of applications and industries, the most prominent ones probably being cryptocurrencies and supply chain management. However, there are concerns around BC, particularly scalability and high energy consumption due to the required computing power. Lastly, its decentralized nature limits oversight and law enforcement, which governments are attempting to address through different approaches.

2.2. Search of Literature

The literature search was conducted across several databases, including Google Scholar, EBSCOhost, Elsevier’s Scopus, Clarivate’s Web of Science platform, JSTOR, and Libsearch (a platform provided by Copenhagen Business School), alongside manual searches in specific journals known for publications on the topic. The search covered literature studies published between January 2010 and December 2023 to ensure relevance and timeliness. Various combinations of keywords were used to find research that matched the paper’s objectives. Excerpts of these are as follows: “Artificial intelligence AND food industry”, “Artificial intelligence AND food AND value chain”, “Artificial intelligence AND food AND sustainability”, or “Artificial intelligence AND food AND strategy”. In addition, a newer tool, ChatGPT, was also experimentally used to find articles revolving around AI and sustainability within the FI.
Figure 3 shows the literature selection process applying PRISMA (Preferred Reporting of Items for Systematic Reviews and Meta-Analysis).

Figure 3. Source: own illustration adapted from Page, M.J., et al., 2021.

2.3. Analysis

After the initial identification of relevant articles, these were further screened based on their titles and abstracts. Only articles deemed pertinent to the research focus were selected for an in-depth review and subsequently integrated into the literature review. Data extraction was performed using a standardized form to ensure consistency, capturing details such as the author(s), publication year, research design, sample size, and key
findings. This standardized extraction facilitated a systematic comparison and synthesis of the studies.

The analysis employed a thematic synthesis approach, where the extracted data were coded to identify recurrent themes. Subsequently, these themes were grouped and synthesized, providing a comprehensive overview of the literature. This approach allows for the identification of patterns, commonalities, and divergences within the research findings.

The systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. PRISMA is a rigorous framework designed to enhance the clarity and transparency of reporting in systematic reviews and meta-analyses. It involves a four-phase process: identification, screening, eligibility, and inclusion. Initially, potential studies are identified through database searches. Next, the studies undergo a screening process based on predefined criteria and an eligibility assessment to determine their relevance. Finally, the studies that meet all criteria are included in the review. This methodological rigor ensures that the review process is comprehensive, unbiased, and reproducible.

It is important to note that this review is limited by its focus on English-language, peer-reviewed journals, which may result in the exclusion of relevant studies published in other languages or non-peer-reviewed formats. Furthermore, the rapid evolution of AI technology means that some of the latest developments might not be fully captured. Despite these limitations, the thematic synthesis approach provides a structured and detailed overview of the field’s current state, highlighting key themes and identifying areas for future research.

3. Results

This literature review provides an overview of the themes and content covered in studies surrounding AI and sustainability within the FI, focusing on recent years. It begins by clarifying the scope of AI. It continues with a description of AI’s role within the FI, followed by examples of AI applications. Next, some of the most commonly raised challenges are listed, and sustainability themes about AI are covered. Finally, the last two sections summarize the literature and discuss the gaps and outlook.

3.1. Clarifying the Scope of AI

Since the technology surrounding AI and related terms such as big data or ML is continuously evolving and in relatively early phases [23], some uncertainty remains around the vocabulary used. This applies to the meaning of the terms and the context in which they are used due to the range of perspectives available. However, they can be linked to parts of the process chain, i.e., data collection, data storage and transferring data analysis, and data visualization [24].

As no universally recognized definition of AI and its related vocabulary exists, the various terms will be explained below in the manner in which they have been commonly used throughout the literature. However, a simplified overview of the key terms could be the following: big data is used for data acquisition, blockchain is used for data security, and AI is used for data processing [24].

The field of AI is understood to be mimicking human intelligence [25]. Therefore, other concepts like ML and deep learning are also considered to be included when talking about AI. A subsection of AI is rule-based AI, which, as the name indicates, runs based on pre-defined rules, usually in the form of if–then statements. It is a comparatively simpler form of AI than the ones described below and can only handle limited complexity.

ML is a subfield of AI based on the idea that computer systems are taught to recognize patterns and make predictions and decisions through various methods and algorithms using data to fit models [3]. Traditionally, these systems were programmed to conduct a specific task; however, with ML, the approach is to train them more broadly and thus offer benefits, including increased automation, accuracy, and adaptability. Deep learning (DL) is a subset of machine learning (ML) and consequently a narrower approach. The
main differences between ML and DL lie in the data type and size they can process and the complexity of the various models. ML typically has a simpler, one-layer structure. At the same time, DL can process multiple layers simultaneously [26] and is thus able to solve more complex problems and be used in image and speech recognition.

For the sake of simplicity, the definition by Baker and Smith (in the review by Zawacki-Richter et al. [27]) is used, defining AI as “computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving”. Hence, it will be understood to be a broader concept encompassing numerous technologies, such as ML and DL. While a concept such as a blockchain would typically be considered separately, this paper will not distinguish between the abovementioned terms due to the high-level view; instead, it groups all the technologies above together.

First coined by Kevin Ashton in 1999, the Internet of Things (IoT) is a technology paradigm contemplated as a network of digitally connected devices and machines. Here, the digital connection of devices, systems, and humans occurs over the Internet. Corresponding processes collect data, which can be used to track and control different devices to optimize their use.

Big data typically involves collecting large and complex data sets and originates from different sources [28]. Next to the characteristics of high volume and variety in data format, it is also known for its velocity. That is, it is close to real-time collection speed [29]. The amount of data requires significant storage and sophisticated technology to process and gain insights. Two of the main concerns that go hand-in-hand with big data revolve around data security and privacy.

Regarding data storage, cloud computing and its related extensions offer an alternative to local data storage. It has also become particularly relevant with the rise of big data that requires management [30]. Users can store and access data remotely through a network of remote servers, typically offered as a service by different providers. Cloud computing has five technical characteristics: large-scale computing resources, high scalability and elastic shared resource pool, dynamic resource scheduling, and general purpose [31]. Its benefits include increased reliability, security, flexibility, and accessibility.

3.2. The Role of Artificial Intelligence across the Food Value Chain in the Industry Context

Different terms have been used throughout the literature to coin the integration of AI within the FI. For example, the broader term industry 4.0 led to the emergence of the new term food industry 4.0 [3], which is often used in connection with the smart factory [32], a concept typically describing the combination of various technologies, thereby creating an interconnected, flexible, and adaptive manufacturing capability [33].

The FI was considered a traditional, low-technology industry, categorized as non-research intensive [34]. However, it is recognized that the competitive environment contributed to the FI’s adoption of new technologies and innovations, and spill-over effects from other industries also led to adoptions within FI [35]. At the same time, the recent hike in AI-related research mentioned in the introduction is further proof of the industry’s advancement. Historically, the timelines of the related areas of nutrition and food chemistry, food analytical methods, and AI have overlapped and, in the late 2010s, started to develop significant synergies [26].

Based on the bibliometric analysis by [5], there have been three growth phases of AI research within the agri-food industry context. In the first one (2002–2006), the main themes revolved around robots, algorithms, and automation, while the second one (2007–2016) centered around AI-powered robots. In the most recent phase, from 2017 onwards, the focus has been on AI themes, including big data, the IoT, ML, and DL.

Various categorizations within the FI exist when applying AI throughout the value chain, with some being (1) smart farming, (2) smart transportation, (3) smart processing, and (4) smart distribution and consumption. Marvin et al. [18] use a similar division, listing the respective challenges and corresponding AI solutions within, e.g., processing and distribution.
3.3. AI Applications throughout the FVC

There have been different ways to structure AI applications and determine their role throughout the FVC. While this overview remains focused on similar areas of application to those chosen by Mavani et al. [18] go into much more technical depth, introducing terms such as fuzzy logic and near-infrared spectroscopy, and Addanki et al. [22] lists applications by sub-industries like bakery or fruit and vegetables. Meanwhile, Misra et al. [36] are among the few authors that list them the other way around, namely beginning with a technology like ML and describing how it can be applied in agriculture and the FL.

While food processing and packaging consist of various steps, implementing sensors and other (real-time) data sources allows for an optimized processing and manufacturing process, as temperature or other parameters can be adjusted for the best and most consistent results [21]. Some elements require human input, which is time-consuming, inefficient, and inaccurate [36]. When AI is introduced, this can reduce errors and increase speed, while it is acknowledged that the variance throughout certain foods is challenging [4,11]. The machines required for other parts of food processing can also benefit from AI through predictive maintenance and ensuring optimal output and use of the machines [37]. Another innovation is AI-based 3D food printing, which is very customizable and can yield high-quality results [38]. For a more detailed view, Kumar et al. [4] have conducted a more in-depth review of key applications in food processing.

Many studies on FI and AI applications revolve around food safety and food quality [39]. The placement of this area within the FVC is less specific because it stretches across the entire FVC and is conducted continuously throughout the different functions.

Following incidents such as the E. coli outbreak in 2018, where large amounts of food were disposed of due to public health concerns, food safety has become increasingly important to mitigate risks and prevent similar outbreaks [36]. Speed in outbreak detection is one area where, for example, blockchain technology can be much quicker than conventional methods; the discrepancy in traceability speed was multiple days compared to mere seconds through technology [40], which in turn impacts how soon and how accurately the according actions can be taken and how many people will be affected by them. Other applications entail detecting defects or damages through monitoring [30], which would replace currently used methods that typically require more labor, take a longer time, are typically destructive, and usually only spot-check [41–43].

Throughout the supply chain, efficiency can be improved while waste and perishability can be reduced, which is where AI comes in [44]. Forecasting, monitoring, inventory management, and price control are all tasks where AI can be integrated [4]. Similarly, temperature control for fresh food can become much more precise [45].

An essential area where blockchain technology can be used is to improve accountability and traceability throughout the supply chain, thus ensuring more transparency [36]. Other benefits take shape through increased consumer trust and improved brand image through product quality and safety [46]. Food authenticity is closely linked to traceability, with the electronic nose technology being one application example that can help identify a product’s species, geographical origin, and manufacturing process through sensors [47].

Applications in logistics and distribution within the FL are similar to other industries, apart from the higher time sensitivity due to the perishability of the products [48]. Thus, areas where AI can be helpful, also named smart logistics, are reducing costs and delivery times through better routing, scheduling, and tracking of the delivery performance [21]. Automation can also help cut operational costs through automated guided vehicles, while information sharing through the cloud allows for real-time information access by different stakeholders [30]. This is especially useful due to increasingly complex customer orders characterized by a low quantity and high variety.

Many studies and AI application examples exist for this part of the food value chain. Especially when it comes to better understanding and predicting consumer behavior and preferences and discovering trends, AI can be useful to analyze social media activity or better tailor marketing campaigns and tweak marketing strategies [4]. Also, in product
development, much progress can be made. While companies used to depend on insights from isolated surveys, they can now leverage AI to collect customer information and improve the success rates of new products [4].

3.4. Challenges and Drawbacks

Since AI offers solutions and opportunities, the challenges and drawbacks must also be illustrated. Dora et al. [49] applied the same grouping to the success factors that influence AI adoption in the FI for a more structured overview.

The most evident obstacles to AI adoption are centered around technological issues. Highlighting a few of these, data availability and the related quality are one initial hurdle that needs to be surpassed before any following steps that lead to valuable insights and results can be realized. Currently, necessary data might still be unreliable or need to be collected in the first place, thus severely limiting any further applications. Related to that, the required infrastructure is not yet in place, which will also take a significant amount of time to set up [50]. The security of data in the form of cybersecurity is also essential, as their value could make companies targets of criminal activity [18]. The complex nature of the technology requires hardware and software, which complicates the implementation of such solutions [24]. Furthermore, while cost-savings can likely be achieved in the long run, the development costs can be very expensive [51]. They may not necessarily be perceived as attractive compared to existing solutions.

Especially for smaller organizations, the aforementioned costs related to developing or purchasing AI technologies, including infrastructure and equipment as well as training employees or hiring experienced ones, can be a big challenge. When it comes to the following steps, organizational culture poses another hurdle, since the company needs to be open to adapting to the changes being implemented, which partially depends on the buy-in from management [49]. Lastly, the strategy and the vision must be strongly linked [52] to ensure effective integration of the technologies.

As can be expected with disruptions, they always go hand-in-hand with resistance. This could stem from entire organizations but also individuals. Reasons for resistance could be a lack of information, understanding, and mistrust, especially when regulation around AI use is still under development [50]. The fear of displacement or job loss by machines is an additional factor to consider [53]. Thus, accepting will take time and delay the adoption process [49].

The opposite of a lack of regulations could also be an issue—that is, when policies around AI are limiting and restraining to an extent where adoption and innovation are hindered and made even more complicated and thus less attractive. Another reason for slower or lesser innovation within this area could arise from vendor lock-in [18], where customers depend on a specific vendor. In return, there are lower incentives for continuous innovation. Also connected to vendors are interoperability issues. Without regulation ensuring standardization and compatibility of the various solutions due to lack of collaboration, flexibility and implementation are limited for enterprises [24].

Within the broader topic of sustainability, there are various recurring elements. Some of the most notable ones are challenges and solutions related to the introduction of AI and the role of stakeholders.

Challenges primarily revolve around an increase in inequality from reinforcing existing biases and discrimination, but a rift in society between adopters and non-adopters is of concern (Marvin et al., 2022 [18]). Along the same line of thought, social inequalities could widen (Ryan, 2022 [17]), as resources and technological access strongly differ at both the country and company level. Other challenges are job displacement and unemployment, as specific tasks that workers currently conduct could be automated in the future [16]; possible higher energy consumption and emissions related to the use of more servers and machines; and data privacy and security concerns [36]. Concerns also remain around the abuse of AI to improve profits while disregarding other sustainability implications when regulations and oversight are not fully in place, taking the fast development into account [54]. Thus,
while adding AI would be beneficial from a profitability perspective, the improvements could come at the cost of the environment if it is not actively considered, for example, due to harmful practices [50].

While it is highly unlikely that an all-encompassing AI solution would solve all sustainability-related problems, various smaller innovations combined could play a big part in enabling the food value chain to become more sustainable [6]. One area where the application is already evident is improving transparency and traceability of products from farm to table and ensuring the various steps were conducted responsibly [55].

Since the food value chain involves many stakeholders, multiple studies also discuss their role while acknowledging the need for further research [56]. A lack of awareness and knowledge around the subject makes it difficult for them to act optimally; thus, increased visibility through campaigns and education around the topic is suggested [21]. Furthermore, decision-makers have difficulties comprehending decisions made with the help of AI, as the process tends to be opaque. In addition, tools need to be developed that encompass all relevant stakeholders and the dimensions and context of complex issues around AI (see Figure 4). Suggestions that tackle some of the problems mentioned above are the development of a common vocabulary that all stakeholders can access and use for discussions [57] and a knowledge-sharing platform accessible to all stakeholders, as suggested by Mosal and El-Barad [58], that fosters collaboration. Enhancing stakeholder engagement through AI can encompass strategic initiatives to deepen interactions and improve satisfaction across all touchpoints. Key strategies can include personalizing communication using AI analytics to tailor messages and offers to specific stakeholder groups, such as consumers and suppliers; enhancing supply chain transparency with blockchain integration; and employing interactive AI-driven platforms for real-time support and feedback. Collaborative AI development and comprehensive training programs empower stakeholders by involving them in the technology’s deployment and understanding. Implementing effective feedback mechanisms and promoting sustainability initiatives via AI fosters trust and encourages active participation, ensuring that AI adoption aligns with stakeholder needs and enhances overall engagement.

![Figure 4. Exemplary stakeholder overview. Source: own creation.](image_url)

The use of AI in management is another avenue that research suggests exploring [16]. Since AI can support and improve a company’s decision-making processes and strategy, inter alia through more precise risk assessments and evaluating all possible options, it can also contribute to making the overall company more sustainable in a top-down manner [6]. Lastly, the significance of an integrative approach is stressed, where sustainable AI solutions should be integrated into the FI, and SDGs and their interconnections need to be acknowledged [21].
3.5. Gaps and Outlook

Integrating various solutions holistically is what is currently left to explore and where more research is needed. More research is required regarding strategy implementation and managerial implications from a governance perspective. Lastly, while different stakeholders increasingly consider AI and the FI, there is still a lack of research considering the impact and solutions to facilitate their exchange.

Looking forward, various topics are going to become increasingly relevant. On the technology front, there is the development of more advanced AI algorithms [59], while simultaneously, debate is also rising on how to handle these new technologies, as already witnessed by the controversial letter penned by various AI experts and business leaders, including Elon Musk and Steve Wozniak, demanding AI labs to pause training of AI systems that are more powerful than GPT-4 for at least six months [60]. Moreover, the integration of AI with other related technologies and the hurdles when it comes to advanced implementation will become more pressing. It is also highly likely that there will be an increase in interdisciplinary collaboration [61], as experts from different fields have similar issues to solve. Lastly, while already present, sustainability will also play an increasingly integral role in itself and within AI. Therefore, it can be expected that solutions directly related to improving the sustainability of different industries [62] and therefore the FVC will soon emerge.

4. Discussion

The contribution of this paper to the literature on AI developments within the FI and their impact on sustainability is twofold. On the one hand, the literature review summarizes the latest research on the topic until now, which is especially relevant because of the fast pace of technology and recent breakthroughs. Key themes like the importance of data or the implications for human resources are identified, existing themes in research are confirmed, and others are added through the emergence of new insights. In addition, the paper contributes to the discourse around several concepts that are not uniformly defined, such as the term AI itself or what the FVC consists of. On the other hand, it especially advances research through its specific focus. Additionally, it takes on a broad view of the entire FI, which is beneficial for researchers in other fields with little to no prior knowledge, as well as being relevant to various researchers within it because of its generalizable insights and accessibility to the business community. It is fair to say that Figure 2 comes through when analyzing the literature as to how AI can optimize the food value chain by enhancing data-driven insights. AI can improve quality control with computer vision systems and optimize operations to reduce waste. For distribution, AI enables route optimization and demand forecasting, ensuring timely deliveries and balanced supply. AI also personalizes recommendations and manages inventory dynamically, reducing waste. Additionally, AI-driven waste management systems sort and recycle food waste efficiently. Overall, AI integration across the food value chain enhances productivity, reduces costs, and promotes sustainability, as Figure 1 suggests. Still, there might be differences in how an AI application might occur, depending on whether a value chain is service- or production-oriented, as Figure 2 indicates.

The paper’s business perspective is another addition to the literature. The integration of AI in the food industry represents a significant opportunity for growth, innovation, and competitive advantage. AI can help reduce costs across various food industry segments, from agricultural production to final product delivery. Automated processes and AI-driven machinery can lower labor costs and improve efficiency. For example, in food processing, AI can automate repetitive tasks like sorting and packaging, saving labor costs, speeding up operations, and reducing human error. It enhances supply chain operations by providing accurate demand forecasting and inventory management. Predictive analytics can anticipate demand trends, helping companies adjust production levels, manage stock effectively, and reduce waste. Real-time tracking and predictive maintenance on equipment can also prevent costly downtimes and extend machinery lifespan, which are crucial for
maintaining supply chain continuity and reducing operational costs. AI enhances risk management by monitoring and predicting potential disruptions in the supply chain, analyzing market conditions, and anticipating regulatory changes. These capabilities enable companies to adapt swiftly to external changes, safeguarding against financial losses and operational hiccups.

Managers should investigate the competitive landscape and have a broad overview of where their company stands compared to others regarding AI integration. This helps during strategy formulation; depending on their position, managers might have to catch up with others or exploit an advantageous leadership position. Additionally, managers must adjust expectations and underline the urgency of what can be done. They must also dispel contorted expectations that are overly ambitious and require years of additional research.

Another consideration is what role sustainability plays when implementing AI, how they impact each other, and how AI and sustainability can be combined. Through an increasing adoption of AI and related technologies, companies can contribute to the SDGs, for example, by reducing energy usage or emissions [63]. Most importantly, managers must recognize how AI and sustainability make their company competitive and help it survive in the long run. However, it is imperative that sustainability is incorporated from the start by taking on a holistic approach and does not become a mere afterthought.

The importance of data and the critical role they play is another aspect that managers must consider. Since data are the foundation for AI solutions, managers need to factor in that AI adoption is directly connected to progress made on data collection. This can take years, as systems have to be set in place to collect the required data, and enough valuable data must be accumulated before further steps can be taken. Next to data collection, preparations must be made to ensure data protection and security are in place. This is not only important for the company itself but also for its collaborations with others. There can be highly sensitive information in the FI that a company might gather through customers, and enough trust needs to be established to allow for that.

Integrating artificial intelligence (AI) in the food industry can present ethical challenges that necessitate careful consideration. Key concerns include the potential for job displacement due to automation, which demands strategies for workforce transition and re-skilling. Consumer privacy is at risk, as AI systems require extensive data to optimize food production and distribution, highlighting the need for stringent data protection measures. Additionally, the inherent biases in AI algorithms can lead to unfair practices or discrimination in product marketing and availability, requiring rigorous bias mitigation protocols. Transparency and explainability of AI decisions, especially those related to food safety and quality control, are critical for maintaining consumer trust and accountability. Moreover, the accessibility of AI innovations must be managed to prevent the widening of existing inequalities in food security. Then the environmental impact of deploying AI technologies calls for sustainable practices to ensure that advancements in the food industry do not come at an excessive cost to the planet. Addressing these ethical issues is essential for fostering responsible AI use that benefits all stakeholders in the food industry.

One of the most apparent parts relates to ensuring sufficient investments in R&D are made and adapted to the resources available and the company’s size. Because of an overall increase in investments in innovation across the FI, this has proven to be particularly important and can be decisive for a firm’s survival in the long run, taking the labor shortage in food processing into account [64], which is where automation will be required. Therefore, managers need to be aware of the importance of successful outcomes and, if their budget allows, provide their R&D department the freedom and flexibility to pursue their ideas. However, smaller, incremental investments can also be a more achievable start for smaller firms, the most important part being that a strategy is being followed, targeting increased innovation and AI adoption.

Sustainability plays a vital role in this, which is why the circularity of products should be considered from the start, and LCA should be used to assess the environmental impact throughout the life cycle of products. Since it is always easier to build sustainability from the
beginning rather than retrospectively, this is where managers can ensure that the company is taking the right direction forward. Another benefit of incorporating sustainability and reporting related ESG or CSR data is that it might help companies obtain more favorable financing conditions [65].

Future research could be conducted on various companies within and outside of the core FVC to gain a complete overview of the FI landscape concerning AI adoption and sustainability. Furthermore, employee insights could increase the representativeness of such findings, especially to determine whether high-level strategies take root further down the chain of command. Other stakeholders could also be included in future research for a more holistic approach, as this gap is also mentioned in other literature studies (see D’Amore et al. and Giacomarra et al. [6,56]). Since the majority of implications synthesized in this paper remain theoretical, another research avenue could be to study whether these hold in practice and to provide an updated review that could yield additional value to managers. Regulations also play an important role, since they have a significant impact on the FI, which is why additional literature studies on the handling of policymakers and the consequences of regulations are also worth conducting. More specific and promising future research within the FI could include AI-driven agricultural optimization, focusing on AI models that analyze weather data, soil conditions, crop health, and more to provide precise farming advice. This could maximize yield while minimizing environmental impact. Another initiative is developing more sophisticated AI-driven robots that can handle delicate tasks in food processing and manufacturing, such as cutting, sorting, and packing different foods. This research could also explore adaptive machines that adjust their operations in response to real-time feedback from their environment. Utilizing machine learning algorithms to automate quality assessment processes, ensuring consistency and safety in food products, could include using computer vision to detect anomalies in food items on production lines. Research on how AI can be used to predict disruptions, optimize routes, and manage inventory more effectively by analyzing patterns in supply chain data would be interesting research. This research could also include real-time, AI-driven decision-making systems for logistics management. Then, creating models that predict potential waste points within the food production and retail chain and suggest interventions, as well as using AI to design innovative food packaging solutions that reduce waste and improve the shelf life of products, would constitute worthwhile research.

**Author Contributions:** Conceptualization, T.O.S. and S.W.; methodology, M.D.-P.T.; validation, T.O.S. and S.W.; formal analysis, M.D.-P.T.; investigation, M.D.-P.T. and S.W.; resources, T.O.S.; writing—original draft preparation, M.D.-P.T.; writing—review and editing, T.O.S., S.W. and M.D.-P.T.; supervision, T.O.S.; project administration, S.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Conflicts of Interest:** Author Miriam Du-Phuong Ta was employed by the company Bain & Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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