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Unleashing the Potential of Digitalization in the Agri-Food Chain for Integrated Food Systems

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Abstract

Digitalization transforms many industries, especially manufacturing, with new concepts such as Industry 4.0 and the Industrial Internet of Things. However, information technology also has the potential to integrate and connect the various steps in the supply chain. For the food industry, the situation is ambivalent: It has a high level of automatization, but the potential of digitalization is so far not used today. In this review, we discuss current trends in information technology that have the potential to transform the food industry into an integrated food system. We show how this digital transformation can integrate various activities within the agri-food chain and support the idea of integrated food systems. Based on a future-use case, we derive the potential of digitalization to tackle future challenges in the food industry and present a research agenda.

1. INTRODUCTION

Information technology (IT): encompasses the use of computers, software, networks, and other technologies to store, retrieve, and process data

Enterprise resource planning (ERP) systems: support monitoring and controlling of business processes

Industry 4.0: combines Internet of Things, cyber-physical production systems, and cloud computing for digitized control and optimization of production

Internet of Things (IoT): describes connected physical devices embedded with sensors and software that exchange data over the Internet

Machine learning (ML): enables computers to learn from data to optimize their performance on a given task

Edge computing: moves data processing and storage closer to the network's edge, i.e., near the data source

Cloud computing: refers to delivering computing services, such as storage, processing power, and software, over the Internet

The food industry needs to undergo dramatic changes in the upcoming years. The COVID-19 pandemic and the war in Ukraine have shown the vulnerability of and the need for more resilience in the food value chains (Alabi & Ngwenyama 2023). Additionally, the awareness of higher sustainability as an answer to climate change influences the food industry, which primarily has to contribute to the UN objectives SGD 2 (Zero Hunger), SGD 12 (Responsible Consumption and Production), and SGD 13 (Climate Action). However, the industry is already highly automatized and efficient. How can those efficient processes be improved and transferred toward sustainable, flexible production?

One answer may be a systemic view of the entire food value chain, integrating all aspects from farm to fork and back in an integrated food systems approach (Ericksen et al. 2012, Van Berkum et al. 2018). This requires integrating not only the company level but especially the information level. Implementing current trends in information technology (IT) can integrate the various process steps and, hence, achieve such a systemic view. The manufacturing industry successfully achieved this through the introduction of enterprise resource planning (ERP) systems in the late 1980s (Rashid et al. 2002), and, more recently, it has been achieved by Industry 4.0 or (industrial) Internet of Things (IoT) technology (Malik et al. 2021). The food industry requires similar developments that enable the transition from automatized production through using robotics in isolated activities toward the integrated, flexible provision of food with the help of digitalization (Rohleder & Minhoff 2019).

In this review, we present and recapitulate various current trends in IT that can help to transform the food industry toward an integrated, digitized systematic approach in which the different aspects of the agri-food chain are viewed as a combined cross-functional approach (Reardon & Timmer 2012). In contrast to existing overviews (e.g., Lezoche et al. 2020, Morella et al. 2021, Misra et al. 2022) that often focus on one or several aspects of the agri-food chain in isolation, we focus on how IT can integrate the chains' stages toward an integrated food system. Our contributions are threefold. First, we explain the relevant trends and technologies in the IT domain (Section 2) and explain how those trends are already established for connecting different functions of the food value chain (Section 3). Second, we present an emerging use case that shows the potential of IT to connect the stakeholders of the agri-food supply chain systematically but is also envisioned to facilitate the transformation to plant-based food alternatives (Section 4). Third, based on the described future use case, we derive the open challenges for applying IT to foster the transformation toward an integrative food system (Section 5). Finally, Section 6 summarizes the article.

2. CURRENT ADVANCES IN INFORMATION TECHNOLOGY

In recent years, new developments in IT have found their path into processes in the industry and provide features that were not imaginable a decade ago: Machine learning (ML) supports the analysis of millions of data points in seconds. The data are collected by sensors connected through IoT technology and edge computing. The data can be processed with the help of cloud computing. Those technologies can also be applied to the food processing context. This section presents several information technologies that will drastically change food production in the current decade.

2.1. Artificial Intelligence, Machine Learning, and Deep Learning

Artificial intelligence (AI) is likely the most prominent digital technology of the past decade. It is broadly deemed a disruptive technology pervading every branch of industry, economy, academia, the public sector, and society. The latest breakthroughs in applying AI technology range from beating world champions in the most complex board and computer games (Silver et al. 2017, Vinyals et al. 2019) to contributing to solving intricate bioinformatics problems such as protein folding prediction (Jumper et al. 2021) and generating human-like and authentic appearing content such as images (Rombach et al. 2022), artworks (Cetinic & She 2022), and entire texts (Van Dis et al. 2023).

The European Commission defines AI systems as referring to "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal" (Eur. Comm. 2019). It is further described as a scientific discipline with several approaches and techniques. One of those approaches is the challenge of enabling machines (or computer systems) to learn—better known by the term ML.

Artificial intelligence (AI): computer systems that can perform human-like tasks such as learning, reasoning, or problem-solving, which are commonly deemed to require intelligence

Digital twin: a virtual model of a product, machine, or process that enables simulations, real-time analyses, or predictions

Deep learning (DL): forms hierarchies of representations of the data using machine learning based on deep neural networks

Following a prominent definition from Mitchell (1997, p. 2), a "machine or program is said to learn, if it improves its performance, measured by a performance measure *P*, on a class of tasks *T*, with increasing experience *E*." This means that in contrast to the conventional programming of computers, using ML, a computer can find a solution to a given problem by itself when provided with enough data or trials. Ways to collect data are manifold. However, recent advances in sensor and IoT technology, combined with modern digital twin concepts from Industry 4.0, are essential to leveraging AI's potential in adding value to the vast amounts of (big) data we can collect these days (see Sections 2.3 and 2.5).

A particularly prominent field of ML is known as deep learning (DL) (LeCun et al. 2015). What makes DL specifically effective is the insight that a cascade of various numbers of deeper layers can form hierarchies of representations of the data input, which is advantageous when learning complex patterns from high-dimensional data. This leads to the core capability of DL techniques to construct high-level features from low-level ones in a self-learning fashion (also referred to as representation learning), given that enough data exist to train such DL models.

Today, most DL models are based on artificial neural networks (Rumelhart et al. 1994). Artificial neurons have been researched since the early 1950s by Rosenblatt (1958), and when stacked and layered together, as inspired by the brain, these neurons form connected networks that can represent and model (in theory, any) nonlinear relationships (Hornik et al. 1989) by adjusting the connection strengths (also called weights or parameters in the literature). One of the areas most influenced by DL is computer vision. Although artificial neural networks for vision tasks have been actively researched since the 1970s (e.g., Fukushima 1980, LeCun et al. 1989), starting with the introduction of deep convolutional neural networks such as AlexNet in 2012 (Krizhevsky et al. 2012), a new impetus occurred in the computer vision community. Pattern recognition and prediction based on image data captured by camera sensors constitute an often-preferred way of process monitoring due to their nondestructive means of capturing system states. That led to DL-based computer vision being one of the main forces in bringing AI technology to many industry branches, also comprising agricultural production and food manufacturing (see Section 3).

2.2. The Hunger for (Big) Data

However, increased recognition capabilities and predictive model capacities facilitated by DL come at a cost, with data being the currency. Collecting vast amounts of data using monitoring systems and sensor technology is not an issue at first glance. However, in most cases, analysts are interested in predicting specific target values from observed sensory data. To train DL models to predict specific categories (classification) or continuous values (regression), a sufficiently large amount of training data must be collected and annotated by a domain expert. The needed annotations represent the ground truth, which is often not straightforward to measure automatically without human expertise. Therefore, efficient training and getting the most out of scarce data sets or large unlabeled data pools are highly active topics in DL research.

Big data: refers to applying advanced information processing technologies and data analytics to extract valuable insights and patterns from high volumes of potentially unstructured data

Cyber-physical systems: interconnected physical and software components, both intertwined by an intelligence for control of the physical components

Furthermore, despite being in the digital big data (De Mauro et al. 2015) era, big data alone is not sufficient. In most business cases, ML models, including DL, need structured data. Of course, ML models exist that extract information from unstructured data such as texts or websites. However, the need for idealized (typically, tabular) data representations becomes the standard case when brought to commercial use and production. Paired with the need for ground-truth annotations, data collections appearing vast and big can quickly become small in ML terms (Kitchin & Lauriault 2015). The excessive hunger of modern data-driven AI models for vast and idealized data constitutes one of the most challenging issues because it strongly influences the achievable quality of data-driven models as obtained by ML and DL.

2.3. Internet of Things, Cyber-Physical Systems, and Sensor Technology

IoT technology combines two streams of IT: miniaturization and connectivity. Computational devices have become smaller and smaller; consequently, it is now possible to equip everyday devices with computers to make them smart (Ashton 2009). IoT devices are connected, i.e., they can exchange information and act upon that. IoT devices can collect information about their environment using sensors and react to new environmental conditions.

Cyber-physical systems consist of tightly integrated physical and cyber components interconnected through one or more networks (Baheti & Gill 2011). The cyber components comprise computing and communication facilities for monitoring, automating, and controlling physical systems and processes (Lesch et al. 2023). In the production context, cyber-physical production systems describe a dual system in which physical operations are modeled in a virtual representation of the real world (Jeschke et al. 2017). Those enable decentralized decision-making, real-time communication, and collaboration among various entities, including humans, over the Internet and IoT components.

Sensors can be connected to IT systems [e.g., e-nose systems (Tan & Xu 2020)], or integrated into the production line for process monitoring/control. They can also be integrated into food packaging. There exists a variety of sensors that might be relevant in the food domain, such as gas sensors or biosensors, that allow conclusions about perishability. CO_2 concentration can be measured using nondispersive infrared sensors or chemical sensors; infrared sensors and electrochemical, ultrasonic, and laser technologies are used to detect the oxygen concentration. Another type of sensor is a biosensor based on receivers made of biological materials such as enzymes, antigens, hormones, and nucleic acids. Müller & Schmid (2019) describe the recent state-of-the-art in sensors for packaging.

2.4. Cloud Computing, Edge Computing, and Fog Computing

Technological innovations like cloud, edge, and fog computing have reshaped how we process, store, and access data. Cloud computing refers to delivering computing services, such as storage, processing power, and software, over the Internet (Qian et al. 2009). It offers scalability, cost-effectiveness, and accessibility from anywhere with an Internet connection. Edge computing moves data processing and storage closer to the network's edge, near the data source. This reduces latency, minimizes bandwidth usage, and allows real-time data analysis, benefiting applications like IoT and autonomous vehicles (Cao et al. 2020). Fog computing combines aspects of both cloud and edge computing, extending cloud services to the edge of the network (Chen et al. 2017). It leverages local edge devices to process and analyze data while relying on centralized cloud resources. The three concepts are interrelated, with edge and fog computing complementing cloud computing to optimize performance, data management, and overall efficiency in a decentralized computing environment (Escamilla-Ambrosio et al. 2018).

Blockchains: act as decentralized data storage for sharing data between the participants

2.5. Industry 4.0, Industrial Internet of Things, and Digital Twinning

Industry 4.0 combines cyber-physical production systems, IoT, and cloud computing (Kagermann et al. 2011). Although the term Industry 4.0 is primarily used in Europe, the overlapping concept of industrial IoT, mainly used in the United States, describes advances in big data, cloud computing, and networking of machinery in the industrial sector (Jeschke et al. 2017). Industry 4.0 does not focus on a single process or technology but integrates all processes, resulting in the smart factory: an integrated production process that is highly flexible due to self-organized, connected machines and intelligent software (Wang et al. 2016).

A key element of Industry 4.0 is the digital twin: a virtual model of a product, machine, or process that comprises its selected characteristics, properties, conditions, and behaviors utilizing models and information created with data collected by sensors that enable simulations, real-time analyses, or predictions (Verboven et al. 2020). A digital twin system facilitates the generation of various digital twins, which can model different aspects or perspectives.

2.6. Blockchain Technology

Blockchains, known from cryptocurrencies such as Bitcoin, act as decentralized data storage where the data are shared between the participants (Kamilaris et al. 2019). Because changes are logged and validated with hash functions, blockchains are nearly not manipulable. Hence, blockchains are a promising approach to enhance traceability in food supply chains and could assist in determining and sharing the food quality to improve the processes and reduce food waste. The possibility of combining a blockchain-based verifier with the digital twin application is worth mentioning to validate and secure the data (Bottani et al. 2020). One often-named issue for blockchains is the postulated energy demand of blockchains. However, this mainly relates to the application of blockchains in cryptocurrencies, where participants have to solve computationally intensive tasks to gain more cryptocurrency shares. Information storage does not require more energy than other distributed, redundant systems.

3. INFORMATION TECHNOLOGY FUNCTIONS AND APPLICATION IN THE FOOD SYSTEM

This section focuses on several essential functions across the food supply chain, starting with agricultural food production. We target functions in which we see a remarkable potential for integrating IT and new digital technologies in relation to the current state of industrial production in the Industry 4.0 context.

3.1. Smart Agricultural Production

IT entered the agricultural production sector quite some time ago. With the management concept of precision agriculture having developed since the 1990s, the utilization of IT in agriculture has become a de facto standard. Today, terms such as smart farming, digital farming, and farming 4.0 are omnipresent but often not sharply distinguished (Balafoutis et al. 2017, Herlitzius et al. 2022). This might be because all concepts share essentially the same goals precision farming has been pursuing ever since: making the most efficient use of input resources (e.g., fertilizers, herbicides, or water for irrigation), i.e., applying them only in the required amount at the right time in the right place over the cropping season through exploiting field-specific data and information that enables site-specific treatments and improved planning. This ensures safeguarding agricultural productivity under the challenging conditions and adaptation requirements imposed by climate change and progressing environmental degradation. The things that have changed, however, since the inception of this concept are the available technological advances that have emerged. For instance, intelligent sensors that allow for real-time and in situ field condition measurement are used for recommendation or semiautomated adaptation of machine configurations. This led to established concepts such as variable rate application and section control (Clark & McGuckin 1996; Shockley et al. 2011, 2012).

The idea and goals behind precision, smart, and digital farming are driven by the insight that field conditions vary in space and time and, thus, exhibit heterogeneity. The same holds for the managed objects (crops or animals); i.e., their conditions and demands change dynamically over time due to the highly complex biophysical interactions with their environment. Accordingly, the agricultural domain can partly be considered unpredictable and thus complicated to model and control. For the same reason, Bechar & Vigneault (2016) deem agriculture one of the most challenging domains for intelligent machines or robots.

Therefore, smart agricultural production goals can only be reached when IT and digital tools are leveraged. Spatially exact positioning can be accomplished today up to a precision of a few centimeters in the fields using Real-Time Kinematic (RTK) positioning technology. This allows tractors and robots to autonomously navigate and drive through the fields without human intervention.

Farm management and information systems (FMIS) (Bökle et al. 2022, Fountas et al. 2015) are software systems that allow for storing and processing agricultural data, documentation of agricultural processes for cross-compliance, tracking of resource or farm machinery utilization, or planning through creating application maps for, e.g., fertilization or plant protection measures. FMIS are related and usually make use of geographic information systems to visualize farmers' fields and overlay these top-down visualizations with application map or soil map layers to allow for planning site-specific treatments (Herlitzius et al. 2022).

Since the advent of new digital technologies such as AI, IoT, and cloud computing, new technological concepts have become possible and have entered the agricultural sector (Misra et al. 2022, Osinga et al. 2022, Paraforos & Griepentrog 2021). The potential of digital farming in agriculture is well-elaborated in the literature (see, e.g., Baerdemaeker 2023, Chaterji et al. 2021, Elbehri & Chestnov 2021, Liakos et al. 2018). In the following, we therefore provide only a brief overview of innovative AI-facilitated applications contributing to sustainable, secure, and highly precise agricultural food production (without any claim for being exhaustive).

Weed detection and precise weed control by means of spot spraying (Allmendinger et al. 2022, Gerhards et al. 2022) or mechanical removal (e.g., Reiser et al. 2019) can be performed by intelligent devices such as smart sprayers or robots (Bechar & Vigneault 2016, Paraforos & Griepentrog 2021).

Apart from weeding and hoeing, agricultural robots in the fields also exist to take over tasks such as seeding (e.g., Blender et al. 2016) or harvesting (e.g., Arad et al. 2020, Zhou et al. 2022) and have done so already with high degrees of autonomy. Furthermore, specialized robots are being developed for conducting highly autonomous plant phenotyping (Mueller-Sim et al. 2017) or vegetation monitoring (Ahmadi et al. 2022; Lüling et al. 2022, 2023) on the fields or in indoor farming applications (see, e.g., Smitt et al. 2021). Spatiotemporally high-resolution monitoring and high-throughput phenotyping of crops are of high importance for plant breeders who create resistant variants of crops and farmers to allow for site-specific or plant-individual treatments and thus safeguard the yields.

Remote sensing applications utilizing AI to analyze and support the annotation of images taken by unmanned aerial vehicles are envisioned to detect plant stresses such as pathogen infestations (e.g., Chin et al. 2023), or are proposed to map weed occurrence (e.g., Sa et al. 2018 and Boysen & Stein 2022), for early crop growing stages.

An essential tool for counteracting food security issues is AI-supported yield prediction (Heil et al. 2023, Srivastava et al. 2022). With ever-more-accurate predictive models based on publicly available satellite and weather data, agencies could, for instance, predict in what regions yield shortcomings are to be expected and can invest early in measures such as importing food to threatened areas.

Next to crop production, new digital tools and sensing systems have demonstrated high potential in digital livestock farming: Farmers today can significantly benefit from animal health monitoring (Bao & Xie 2022, Zimpel et al. 2021) using posture detection (Riekert et al. 2020) and behavior analysis (Arablouei et al. 2023, Lardy et al. 2022) or monitoring of milking performance and prediction (e.g., Seymour et al. 2022).

Smart primary food production using digital tools is integral to a future Food Industry 4.0. Smart sensors on the fields and in animal housing deliver valuable data feeding into digital models and digital twins (Pylianidis et al. 2021, Verdouw et al. 2021; see also Section 3.3). We return to this use case in Section 4. This allows, in the subsequent step, information extraction and knowledge creation over the entire primary food production process, which in turn facilitates food traceability (see Section 3.5) and delivers further valuable information to succeeding food manufacturing, delivery, and sales steps, i.e., from farm to fork.

3.2. Intelligent Food Processing

Several applications in food production are only feasible with AI. Especially in the field of image processing, it leads to ever-new solutions. Classic pick-and-place applications, for instance, rely on intelligent vision systems that provide robots with gripping positions, as well as the determination of size, geometry, contour, shape, and density of products, enabling accurate packaging or processing (Lobbezoo et al. 2021). The trend toward automation with optical methods is pervasive in Industry 4.0, not only in production lines but also increasingly in quality control (Lin et al. 2023). Currently, DL algorithms have become state-of-the-art for picture detection (Zhu et al. 2021).

With the integration of AI, companies also equip their inspection devices to enhance food safety (Qian et al. 2023) and reduce waste (Harvey et al. 2020). By using AI, the metal detectors of these providers can nearly eliminate product effects in foods with high inherent conductivity, preventing false alarms. This scenario is common in protein products like meat and cheese, metalized packaging, or high salt and moisture content products. Regarding technological innovations, foreign body inspection is no longer conducted sporadically after food production but is performed directly during the process. If an error is detected, the systems can ideally compensate automatically without the operator's intervention.

AI demonstrates its strengths wherever early detection of quality deviations is necessary. The Future Lab 2030 (Zeh & Türkmen 2023) project team envisions that, through modern data analysis methods, quality characteristics currently measured as samples in laboratories will be captured and evaluated in real time during the production process. In addition to innovative measuring methods, i.e., new types of inline sensors [e.g., based on mass spectrometry (Diez-Simon et al. 2019), hyperspectral detection (Zhu et al. 2020), or gas chromatography (Wang et al. 2020)], AI and ML play a central role in this endeavor. The aim is to capture data on food products' most crucial chemical, physical, and biological processes. All data describing the condition of a food product are collected and mapped with additional data using a digital twin (Koulouris et al. 2021). However, the industry is still cautious in adopting novel and often expensive sensor technology. Furthermore, approaches for digital food twins still need to be developed (Henrichs et al. 2022, Krupitzer et al. 2022).

The cleaning process is a critical aspect of food processing that offers the potential for optimizing time constraints and resource consumption. Cleaning in place (CIP) approaches are often applied; however, those approaches follow fixed, standardized cleaning processes. Hesse (2017) showed how an intelligent, self-learning cleaning system with optical inline contamination sensing could save water and energy consumption. Such approaches rely on innovative sensor technology and AI to interpret the sensor information in real time and optimize the cleaning process.

3.3. Process Monitoring through Enterprise Resource Planning Systems and Digital Twins

Since the 1980s, the manufacturing area has used ERP systems to monitor and control production (Rashid et al. 2002). ERP systems support business processes through specific cross-divisional IT functions. Those systems helped to integrate different business functions across several divisions in companies. Usually, ERP systems are composed of standard modules (e.g., for HR functions) and more specific modules, e.g., for control of manufacturing processes.

The food industry often has different systems that store data from production, laboratory analysis, and product development. Rather than relying on the standard solutions of companies such as SAP or Oracle for the food industry, different customized ERP solutions are available, such as InnoSEP, PDG foodSolution, or JUSTFOOD. In the future, those systems might have the same effects as the ERP systems in the manufacturing industries and can connect the different stakeholders like farmers, distributors, and producers through common systems (Setiabudi et al. 2021, Zadeh et al. 2018). The data stored in the ERP system can also be made available to different stakeholders from individualized perspectives such as dashboards or apps.

Digital twins can support the monitoring and analysis of manufacturing processes (Grieves 2014). The idea is to use the collected data from sensors and the data in manufacturing execution systems (a module of ERP systems) to build a digital model of the product and analyze the influences of the process on the product. However, this is more complicated for the food industry than other industries. The reason for that lies in the product properties: Whereas most products in manufacturing only change their characteristics through process steps, food changes its characteristics independent from the process through biological, physical, or chemical processes within the food product (Krupitzer et al. 2022). Digital food twins have to incorporate models for those changes. Currently, research has started to take this into account (Henrichs et al. 2022). So far, industry solutions that provide an out-of-the-box solution for digital food twins have yet to exist.

3.4. Predictive Supply Chain Management

IoT, especially the application of sensors, can improve the monitoring within the (food) supply chain (Sawik 2013). Consequently, supply chain management can be optimized when integrating a management system such as an ERP system. However, the computation capacity for real-time analysis is often unavailable, especially during transportation. Often, IoT systems are combined with computational resources in the cloud, requiring a stable network connection, which is not guaranteed. Hence, real-time analysis in the cloud might not be feasible.

Real-time analysis has vast potential. For example, it could be used to analyze when a truck drives a bumpy street if there is the potential for damages to the food items due to the movement of the items. Combined with ML, it can also support forecasting food conditions, e.g., proactively determining whether the cold chain could be violated. Alternatively, if the temperature stays stable, it might be possible to adjust the cooling system in the truck to save energy. All those use cases require computational power. There has been a shift of this computational power from the cloud toward the data, hence, using small computational devices close to the location where the data are collected. This is subsumed under the term edge computing. Recent research tries to understand the potential and limitations of this approach (Khan et al. 2019).

Such data analysis approaches also support the long-time analysis of the (food) supply chain. This is important to support various adjustments, which might improve the resilience of the food supply. Furthermore, real-time analysis for immediate reactions to critical events can improve the system's resilience. We highlight the potential of real-time predictive data analytics in Section 4.

3.5. Food Traceability through Blockchains

Sensors can be used to collect different data about food in real time (Zaukuu et al. 2020). These data are stored in databases, which single actors maintain, often the stakeholder with the highest market power. Accordingly, only some actors in the food supply chain have access to the data. This significantly influences the verification of the products' and ingredients' origin.

Blockchains have two crucial characteristics that support their application for tracing items in the food supply chain (Li et al. 2023). First, blockchains are a distributed data structure. Each participant of a blockchain has access to data. Second, data in a blockchain can only be changed with agreement between all parties. Hence, it is immutable, and data manipulation is not possible. Accordingly, blockchains seem to be the ideal structure for supply chain management (Cole et al. 2019) and transparent data storage in the distributed food supply. Accordingly, the blockchain might link all stakeholders and provide companies, but also customers, with an interface for transparent information about the food origin.

However, several open issues reduce their applicability. Blockchains might fit if the food supply chain is a simple chain. In reality, we have several parallel chains (Kramer et al. 2021). For example, when producing a cake, we have several ingredients; all of them would have their blockchain for traceability. After production, the blockchain for describing the cake has to combine all the data. In the end, the blockchain is extended to a network of blockchains. This comes with many technical issues that need to be solved in reality. Kamath (2018) describes the application of the IBM Food Trust blockchain solution in different use cases.

4. FUTURE APPLICATION SCENARIO: DIGITALIZING THE MILK PRODUCT CHAIN

In this section, we want to highlight the potential of IT for generating an integrated food system. We focus here on milk products as an example, as those are one of the product categories that have been heavily changing in recent years and will further change in the coming years. Various societal and environmental changes affect the industry. The calls for animal welfare and the reduction of greenhouse gas emissions result in the need for new plant-based product alternatives (Moss et al. 2022) as well as new types of packaging that potentially influence the durability of the products (Meherishi et al. 2019). Increased awareness of consumers regarding the origin of their food leads to the demand for better traceability and the presentation of the product stories regarding the origin of the products (Petrescu et al. 2020). Furthermore, the demand for renewable energy sources, the energy crisis in Europe, and the need to reduce the entire food system's CO_2 footprint also require the identification of process optimizations. We deem utilizing new digital technologies key to reaching and supporting the transformation toward an integrated food system. **Figure 1**

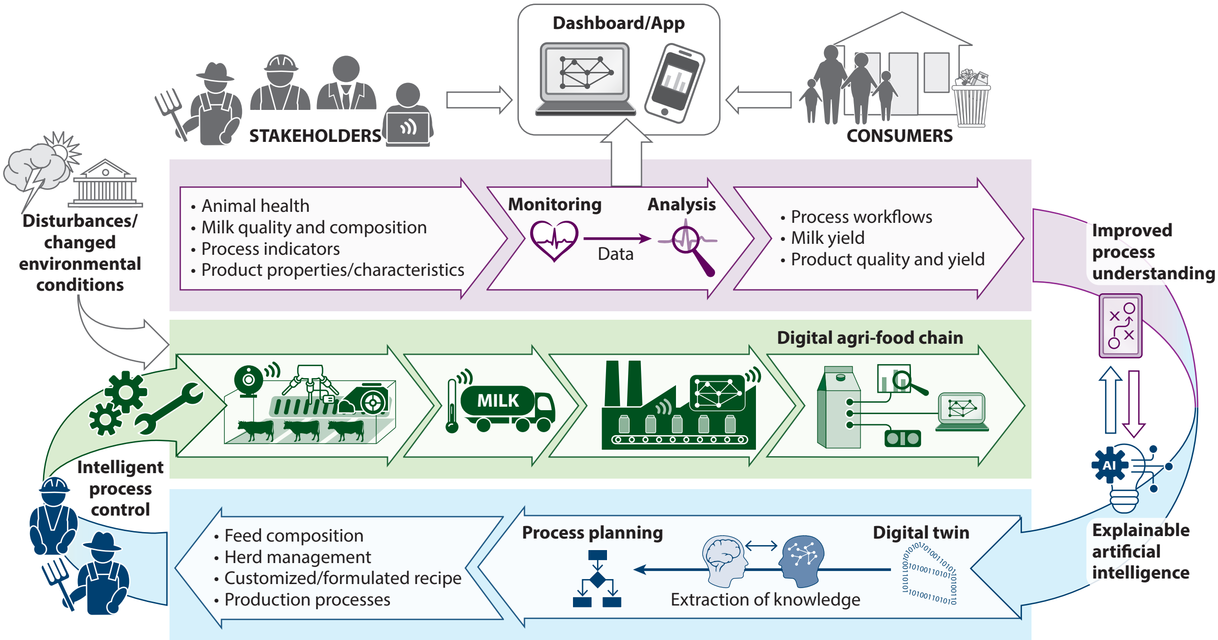

Figure 1

The vision of the digitalized agri-food chain. This system model integrates the different process activities for farming, transportation, and processing (based on the example of dairy products) through the use of information systems and artificial intelligence.

shows an overview of our vision for such an integrated food system approach using the example of the dairy industry. We elaborate on the envisioned potential in the following.

4.1. Real-Time Process Monitoring and Analysis through Edge Computing

Edge computing is a decentralized computing paradigm that processes data closer to their originating source, reducing latency and bandwidth utilization while enabling real-time data analysis and response. In contrast to cloud computing, in which the data must be transferred to the cloud servers first, edge computing supports a faster real-time analysis, given that the respective tasks are computationally feasible. Therefore, cloud computing might complement edge computing, especially in ML. The computation-intensive part of data-driven ML applications, i.e., training the corresponding ML modules, might run on the cloud servers, where computational resources are available, and (historical) data from various data sources can be combined and centrally stored. The trained models can be deployed and executed on edge devices like smartphones, IoT devices, and edge servers. This is referred to as Edge ML (Murshed et al. 2021). Those edge devices are often lightweight in their computational capacity for energy-saving reasons. Still, the execution or inference steps of the ML models are often feasible in real time with low energy demand.

Edge ML brings several advantages, including reduced latency, improved privacy and security (also data sovereignty), and the ability to make real-time decisions without relying on a constant Internet connection. It is especially beneficial when Internet connectivity is limited and real-time, low-latency processing is required. In situ data preprocessing and analysis at the source (on-the-edge) help to identify, monitor, and predict relevant process parameters in real time. Hence, with the help of edge computing, it is feasible to monitor the processes continuously, e.g., in the stall, during transportation, or in milk processing. This generates a holistic, integrated view of the process activities.

Furthermore, explanations for predictive analyses can be tailored to different stakeholders to, for instance, omit confidential data. Algorithms can also provide recommendations for proactive adjustments of process parameters to avoid critical situations, such as early spoilage detection or fouling to prevent intermediate cleanings. This approach fosters a deeper understanding of production processes and potential influences on product quality, allowing for better assessment of downstream impacts and process optimizations along the agri-food chain.

Explainable artificial intelligence (XAI): refers to the capability of AI systems to provide understandable and transparent explanations for their decision-making

4.2. Connecting the Chain Elements through Artificial Intelligence

A systematic approach toward integrated food systems requires the interconnection of the different actors in the food supply chain, which implies interoperability among the different IT systems (Verdouw et al. 2016). For the milk industry, this mainly concerns the farmers, dairies, and retailers. Also, the customers might be integrated. The German dairy Schwarzwaldmilch provides one excellent example related to food, showing the data's power. After scanning a QR code on the milk package, customers can see from which farms their milk was collected (YoY 2021).

Even though the milk industry is highly standardized, milk as an essential ingredient might be difficult because its exact composition is highly dependent on several factors, especially the feeding and treatment of cows. By employing state-of-the-art in situ sensor technology and continuous monitoring of critical process indicators, generating a vast amount of data and information is possible. Examples would be camera-based tracking of the eating behavior of dairy cattle fused with information on feed composition or the automatic measurement of milking performance and parameters by milking robots. In subsequent steps, intelligent digital methods are then deployed to create value, e.g., applying real-time data analytics using Edge ML and informing farmers and operators in later processing steps. Furthermore, the data can be interpreted using ML or DL methods to detect relevant process indicators or anomalies. However, those analyses require a view from farm to fork and back: Leveraging interconnected digital technologies, including IoT, digital twins, and edge computing, coupled with distributed and explainable artificial intelligence (XAI) methodologies can pave the way for a pervasive, automated, and self-organizing agri-food value chain, encompassing consumers and providing feedback to primary producers, processors, and distributors. Applying the systemic process knowledge acquired through AI and data analysis will help plan and realize adjustments to relevant process steps.

One challenge with modern ML, especially DL models, is their inherent complexity and opaqueness. As these models become larger and more complex to improve their performance, they become black boxes, meaning that one cannot extract the inner reasoning of the ML model from input to predicted output. The term explainability in this context refers to the ability to understand and interpret how a model arrives at its predictions or decisions, which is with what the research stream of XAI is concerned (Gunning et al. 2019). We highlight the challenges in Section 5.5. XAI-based knowledge extraction with simulations (using digital twins) can support automated adaptive process control. In the next step, highly interconnected and interoperable software systems combined with automated adaptive process control would facilitate holistic mutual optimizations on the system level rather than the individual chain-element level. For instance, between dairy farmers and milk producers, an intelligent process control system could optimize logistics operations for raw milk delivery (as indicated in the middle box in **Figure 1**). However, this does not mean that humans should be entirely out of the loop; implementing the AI algorithms in intelligent decision support systems with humans making the final decision to adjust process parameters based on a profound analysis of the available data is feasible.

4.3. Digital Food Twins for Product Development and Process Optimization

In the dairy industry, milk composition varies throughout the year. Using profound data analytics and XAI, it is possible to investigate whether these variances are identifiable in the collected data from the cattle sheds and whether they can be attributed to, e.g., feed composition, animal health and behavior, or other parameters. We deem digital twins a promising way to model the dependencies of the milk composition from primary production on the receipt formulation in later processing or on other process parameters.

Furthermore, protein sources are moving from animal to plant origin, driven by concerns about animal welfare and the environmental effects of raw material production (Moss et al. 2022). Digital twins that model and simulate process steps and product characteristics can support this and be the basis for ML-supported reformulation of vegan dairy products. Additionally, we see promising potential in using the digital twin's information to more accurately determine a new product's potential shelf-life based on the observations of similar products and the adjustments of a corresponding existing digital twin for the new product. Also, on even lower levels, the digital twin could model the chemo-physical and microbiological properties of the food (Krupitzer et al. 2022) to simulate the food's perishability. This can contribute to more accurate shelf-life predictions, which are especially important for milk products. Furthermore, it is also feasible to integrate a digital twin of the packaging and, by combining this with the digital twin of the food, to determine the interactions between the packaging and the perishability of the food.

5. RESEARCH AGENDA

In the previous sections, we described the implementation of IT in different functions of the food supply chain and stressed the current and potential future benefits of IT for an integrated approach to monitor and control future food systems from farm to fork. We corroborated this by employing a critical use case, i.e., the digitalization of milk production. In this section, we derive a research agenda of how the goal for an integrated food system leveraging new digital technologies, such as AI, IoT, edge, and cloud computing, can be reached. We summarize requirements for companies and scientists as well as for the education of skilled personnel.

5.1. Understanding Supply Chains as Supply Matrices and Networks

The food supply is often represented as a straightforward supply chain; however, this only partially reflects reality. Take the example of an apple cake: One producer requires several ingredients, such as eggs, flour, apple, milk, etc. Those come from many different producers, each with several other customers. We might also have a mixture of those business activities, e.g., the apple producer might sell some apples to other producers, some to markets, or even some directly to consumers. Furthermore, the consideration and optimization of sidestreams and the end-of-life (of product and packaging) are significant for sustainable food provision. Not only the end-of-life but also lower quality class rated apples (or other raw products) can be sidestreamed directly to upcyclers who themselves trade the upcycled products further along the network. Particular interest can arise if the sidestreams of the products, e.g., from plant-based milk alternatives, might be suitable for producing the packaging materials. Hence, the former simple supply chains are converted into complex supply matrices and networks.

The application of new digital technologies can support dealing with the complexity of these supply structures and further their transition (Yadav et al. 2022). A critical issue in terms of digitalization constitutes the sovereignty of the data involved. At present, data are often stored centrally with the disadvantage that only a few actors have access to most of it, or it is kept locally, meaning many or all actors only have access to data shares. However, both approaches prevent an end-to-end view of the processes, which is crucial for systemic analysis and integrated optimization. Blockchain (see Section 2) seems promising for distributed management and secured data utilization. All actors in the agri-food chain could gain access to the necessary data and can act upon this. This would render end-to-end process analysis through ML and chain- or network-wide optimization possible.

However, this entails technical requirements such as standardized interfaces, interoperability, compatibility, and communication between various information systems. Although other industries already have such standardized processes implemented in ERP systems, the food industry still needs to include such a level of standardization. Future research activities in this regard are required, mainly by the different stakeholders and IT industry, to develop systems adjusted to the requirements of the food industry. Actors that in the future are supposed to conduct such software projects must be educated accordingly and understand the complexity of future digital food systems through developing a systemic understanding of the agri-food network.

5.2. Supporting the Transition to a Circular Economy

In the previous paragraph, we discussed the transition of the food supply chain toward a food supply network. This network is not a forward network; the consideration of sidestreams and end-of-life of products and packaging requires the transformation to a circular economy (Esposito et al. 2020).

Sidestream analysis becomes more and more critical. On the one hand, traceability is an essential aspect in this regard (Kumperščak et al. 2019) to improve the reuse of residues. On the other hand, energy management in production facilities gained more attention recently. Especially in food production, extreme differences in temperature for different production steps exist, e.g., producing bread rolls in which the temperature between baking processes and refrigeration differs by almost 250°C. Such potential can be used within heat exchange networks, where digital twins and ML-based data analytics might help optimize the organization of heat management and sidestreams (Chen et al. 2023, Yu et al. 2022).

Digitalization can also support the transformation from linear supply chains to a circular economy, as the digitization of information supports the (sensor-based) collection and analysis of data for optimizing sidestreams and the end-of-life of products (Chung et al. 2022). Hence, this supports creating a feedback loop, i.e., a circular loop. Future research must also elaborate on the application of digitalization to support the transition toward a circular economy and also extend the perspective toward the bio-based industry beyond food products, especially regarding the topic of sustainable packaging, e.g., replacing fossil-based plastics with biogenous materials from plant residues (Stökle & Kruse 2019). Significantly, sustainable packaging raises further questions, as the new types of materials and packaging influence the durability of the products. Despite its infancy, first approaches already exist that model the packaging and ripening processes in digital twins (Shrivastava et al. 2023). All those aspects concern various scientific disciplines. Hence, interdisciplinary project teams in industry and interdisciplinary education of students are required.

5.3. Enabling Decentralization and Scale-Down by Distributed Artificial Intelligence

The different crises in recent years, mainly the COVID-19 pandemic and also war in Europe, showed the vulnerability of the global food supply chain. Accordingly, companies strive for decentralization of their food supply chains (Alabi & Ngwenyama 2023) to achieve a resilient food supply. Additionally, the demand of customers for local food also shows the growing importance of decentralized food production. Furthermore, there is a trend toward individualized food (i.e., lot size of 1); hence, scale-down activities are becoming more important (Rohleder & Minhoff 2019).

Adaptive systems are software and hardware systems that are able to adjust their behavior at runtime to adapt to changes in their environments (Krupitzer et al. 2015). Such systems can optimize the digitalized processes of food production but also increase flexibility and allow for faster reactions to changes.

Multi-agent systems: computerized systems in which autonomous entities interact and communicate to achieve shared goals or solve complex problems in a distributed manner

Another approach to support decentralization can be multi-agent systems (van der Hoek & Wooldridge 2008). Multi-agent systems are computerized systems in which multiple (autonomous) entities (called agents) interact with their environment and communicate with other agents to achieve common goals or solve complex problems in a distributed fashion. These agents can be software entities, robots, or other AI systems that work together, often exhibiting emergent behavior beyond what each individual agent could accomplish on its own and what would be predictable when looking only at the capabilities of the individual agents at the bottom level. It is further possible to combine the multi-agent systems with learning mechanisms. Often, reinforcement learning is applied in such scenarios (Buşoniu et al. 2010). Modeling the parts of the food chain/network and its involved stakeholders as a multi-agent system has the potential to support the cohesive analysis, optimization, and understanding of the various activities and their interrelationships. Accordingly, we deem research in this direction an integral step toward intelligent agri-food chains for an integrated food system.

5.4. New Interactions: From Farm to Fork and Back

Traditionally, the food supply chain is arranged in the direction of farm to fork, i.e., business-to-customer (B2C). As envisioned in this article, the availability and utilization of new digital tools might completely change those interactions and even reverse their direction [customer-to-business (C2B)] or allow for a cyclic information flow and process optimization, i.e., from farm to fork and back. For example, social media can be an essential point of contact for producers where they can advertise their products (B2C). Nevertheless, consumers can also comment on companies' social media activities or even contact them directly (C2B). Besides the interaction between the producer and consumer, new direct interactions between consumers are feasible via digital media, which must be taken into account by producers. Those interactions include discussions on social media, cooking recipes, and food sharing (Harvey et al. 2020).

Also, the demand for individualized products (and personalized nutrition) increases. This reverts the traditional push-based food supply chain into a pull-based approach or, put another way, from fork to farm. Consequently, producers have to react more quickly to consumers' preferences. Online sales through companies gained higher importance, especially during the COVID-19 pandemic (Dannenberg et al. 2020). This offers companies a new channel of direct contact with customers. For example, Vly, a German company that produces milk alternatives from peas, first offers new versions of products online and collects customer feedback about the product quality (Vly 2021).

The producers must monitor and potentially react to those activities (e.g., through commenting or enabling) and new contact channels. Furthermore, increased customer awareness about the origin of food, which requires traceability (Anastasiadis et al. 2022), strengthens customer influence.

5.5. Increasing Trust in the Digital Food System through Explainable Artificial Intelligence

ML models and simulations encompass three distinct categories: descriptive, predictive, and prescriptive (El Morr & Ali-Hassan 2019). Descriptive models analyze historical data to understand past events and trends. Predictive models use this understanding to forecast future outcomes or generalize to unseen situations. Prescriptive models go a step further, recommending optimal actions to decision-makers to achieve desired results based on predicted (or simulated) scenarios. Using ML and DL often facilitates predictive and prescriptive models (Roy et al. 2022). However, the resulting models of those approaches often have the issue of being opaque and are thus often referred to as black box models.

Generative AI: can create diverse content, ranging from text and images to music, videos, and more

XAI refers to the capability of AI systems to provide understandable and transparent explanations for their decision-making processes (Gunning & Aha 2019), increasing the trustworthiness of these systems. Unlike conventional DL models that operate in a black box fashion, XAI provides human-interpretable insights into how and why AI arrives at specific conclusions. This interpretability fosters trust and understanding (Das & Rad 2020). Improved trust arises from the ability to audit AI predictions, detect biases, and identify potential errors. XAI empowers users to make informed decisions, leading to greater acceptance and adoption of AI technologies.

Simulations might complement XAI to enhance AI model explainability (Feldkamp & Strassburger 2023). By integrating different already existing simulation approaches for food processing (e.g., Barroso da Silva et al. 2020, Wilson & Chew 2023), the transparency and trustworthiness of AI systems in the food sector can also be improved. Hence, combining XAI and simulation allows stakeholders to better understand, validate, and interpret AI outcomes and productively use the results. However, research in this direction remains sparse and thus concludes that further work is required.

5.6. Information Provision through Generative Artificial Intelligence

Generative AI systems can create diverse content, ranging from text, images, music, videos, and more. Large language models such as GPT-3 excel at generating human-like text, enabling various applications of such models also in the food domain. For instance, chatbots in food apps could answer questions about specific foods (about their origin, ingredients, etc.) or give proposals for daily diet plans after being prompted with the preferences of the customers. The publication of ChatGPT simplified access to such textual information. StyleGAN, Stable Diffusion, and DALL-E can produce highly realistic images and create novel visual content based on textual descriptions. First studies revealed the potential for different industries such as software vendors (Ebert & Louridas 2023), finance (Krause 2023), and tourism (Dwivedi et al. 2024). Those industries have in common that the creation and processing of textual information are highly relevant. For the food industry, the first visible works concentrate on receipt provision (Razzaq et al. 2023) or determining nutrition values (Venkataramanan et al. 2023).

However, these generative AI systems also come with certain limitations. One primary concern is their potential to generate misleading or untrue facts (known as hallucination), leading to potentially severe misinformation. Moreover, they might inadvertently amplify existing biases in the data they were trained on, leading to similarly skewed outputs. Ensuring ethical use and addressing these limitations are crucial for the responsible adoption of generative AI systems, especially in the food sector, which concerns every human being. Still, those systems will, by all indications, change not only how we retrieve information but also how we state information. This change and digital literacy must be further incorporated into research and educating students and qualified personnel.

6. CONCLUSION

Digitalization and all its new tools, particularly AI and ML, hold immense potential for revolutionizing the agri-food chain and transforming it into an integrated food system. By leveraging those advanced computational technologies, the agri-food industry can enhance productivity, sustainability, and efficiency across the entire value chain and network.

Starting from primary production, we discussed how AI and ML in smart agricultural production enable farmers to optimize crop and herd management through data acquisition, analysis, and decision-making. Moreover, in the succeeding food processing and distribution stages, digitalization can further streamline operations, reduce waste, or reuse residues in sidestreams, eventually contributing to increased food security and traceability.

However, several challenges must first be addressed to integrate and exploit the envisioned promises successfully. Trustworthiness is a crucial factor, as stakeholders must have confidence in the accuracy and believe in the reliability of these partly opaque technologies. Additionally, data exchange among different actors in the agri-food system requires interoperability through standardized protocols and secure platforms to ensure seamless communication and information exchange. Ensuring data confidentiality for safeguarding data sovereignty is paramount, as sensitive information across different organizations must be protected from unauthorized access. By conducting research and developing innovative methods to overcome these challenges, the agri-food sector can fully harness the potential of digitalization, fostering the transition toward a more resilient, sustainable, and interconnected global food system.

SUMMARY POINTS

1. Artificial intelligence (AI), machine learning (ML), and deep learning offer chain-wide integrated data analytics.
2. Internet of Things (IoT) technology supports efficient and intelligent data analysis and connection of systems.
3. Edge computing enables real-time data analytics close to the sources of the data.
4. Digital food twins need to model the chemo-physical and microbiological properties of the food and have a large potential for traceability.
5. Explainable AI (XAI) offers understandable and transparent explanations to foster trust and comprehension of ML/AI systems.
6. Generative AI can create diverse content, but its potential for food systems is yet to be explored.
7. Modern information technology (IT) can transform the stages in the agri-food chain into an integrated food system. This requires interdisciplinary cooperation between data scientists, IT personnel, engineers, and stakeholders of the agri-food chain.

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