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Review of The Application of Digital Transformation in Food Industry

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Abstract

In recent years, food companies have been facing various challenges related to fluctuating demand and constantly evolving customer and supplier requirements. These challenges have made it necessary for food companies to adapt to new technological advancements and implement new solutions to optimize their manufacturing systems. One such solution is digital transformation, which is a suite of technologies aimed at creating smart ecosystems that can transform industrial processes. Digital transformations are designed to exploit the potential of rapidly advancing information and communication technology (ICT) in the food industry. These include digital tools such as machine learning, artificial intelligence, blockchain, and IoT or the Internet of Things. These technologies have several applications in the food industry, ranging from food supply chain management to food safety, production, and consumption.

Keywords: *Artificial intelligence; block chain; food industry; machine learning; internet of things*

1. Introduction

The agri-food sector forms an influential worldwide manufacturing industry encompassing a vibrant ecosystem of societal-technical innovation (Rowan, 2019). This industry involves a variety of stakeholders, from farmers to food manufacturing and processing companies. One of the key challenges facing the agri-food industry, as the world's population continues to grow, is to enhance or optimize sustainable production and processing methods (Saguy et al., 2018). Agriculture plays a crucial role in the GDP of many countries and contributes 6.4% to the global economy, with some countries relying heavily on this sector (Pathan et al., 2020). For developing countries like Brazil and Indonesia, agriculture is an important driver of future economic growth. Food industry in Indonesia contribute for more than 6.9% from Indonesian GDP and its mean 38.9% of non-oil and gas Indonesian GDP (Yasin, 2022). In contrast, developed economies can use agriculture to expand their international market share of agricultural goods (Mueller & Mueller, 2016). The digital transformation has become an essential tool for advancing the agricultural and food industries, changing traditional food systems into modern, technology-driven systems (Klerkx & Begemann, 2020).

Digital transformation involves using digital technologies to transform organizations and create value, resulting in significant disruptions across global markets and industries. This change is driven by factors such as evolving consumer behavior, digital competition, and data availability. Technological enablers of this transformation include cloud computing, big data analytics, artificial intelligence, mobile technologies, and the Internet of Things (Appio et al., 2021). Digital transformation is also expected to have a positive impact on sustainability, including environmental sustainability, and enhance human health across the food chain (Shahi & Sinha, 2020). The effects of digital transformation are not limited to the food industry and can be observed in other areas such as healthcare and social dynamics.

In April 2018, Indonesia, recognized as a developing nation, unveiled The Roadmap of Making Indonesia 4.0, aiming to dedicate substantial efforts towards narrowing the gap with other countries and adopting Industry 4.0 as a national strategy to enhance competitiveness (Hartarto & Antara, 2018). Although digital transformation is becoming a strategic imperative in traditional industry sectors, several barriers may hinder its adoption. The uncertainties on which Industry 4.0 digital technologies to adopt poses a challenge for investing in such technologies, particularly in the food industry (Moeuf et al., 2018). Besides, there are five main barriers for implementing digital transformation in Indonesia, including food industry as one the priority sector unclear Industry 4.0 policy, insecure data sharing, higher-risk investment, lack of incentive and lack of expertise (Fernando et al., 2022). Therefore, there is a need to understand digital transformation and identify the most suitable digital technologies for each industry sector. Hence, this paper reviews the application of digital transformation in the food industry to guide these industries in their journey towards development.

2. Digitalization

The food industry is currently experiencing a profound digital transformation trend, marked by a comprehensive shift towards adopting digital technologies and data-driven approaches across its entire value chain (Liu et al., 2020). This transformative process encompasses various aspects, including supply chain management, production, distribution, marketing, and customer engagement. Advanced technologies such as artificial intelligence (AI), Internet of Things (IoT) devices, blockchain, and data analytics are being harnessed to optimize operational efficiency, enhance product quality, ensure food safety, and deliver personalized customer experiences (Tabrizi et al., 2019). From smart agriculture practices and precision farming to smart packaging and online ordering platforms, the food industry is leveraging digital solutions to stay competitive, meet changing consumer demands, and drive innovation. This digital transformation trend is reshaping the industry's landscape, fostering greater sustainability, transparency, and responsiveness to emerging market trends and customer preferences (Yaqub & Alsabban, 2023).

There are three steps in the digital revolution, starting with digitization, digitalization, and the last is digital transformation (Figure 1). In the first stage, digitization, the food industry is transitioning from traditional paper-based processes to digital formats. This involves converting analog information, such as recipes, inventory records, and customer data, into electronic databases and files. Digitization lays the groundwork for enhanced data accessibility, storage, and sharing, enabling better organization and analysis of critical information. With digitized data, food companies can efficiently manage inventory, track sales, and gain insights into consumer preferences, setting the stage for more advanced digital advancements (Remondino & Zanin, 2022).

The second stage, digitalization, leverages the digitized data to optimize processes and decision-making. This phase involves integrating digital tools, applications, and software into various aspects of food industry operations. Companies can implement advanced inventory management systems, automated production lines, and digital point-of-sale (POS) systems, streamlining their supply chain, enhancing production efficiency, and improving customer service. Digitalization enables real-time data analysis and informed decision-making, empowering businesses to respond rapidly to market trends and customer demands (Kittipanya-Ngam & Tan, 2020).

The final and most transformative stage is digital transformation, where the food industry undergoes a profound cultural and strategic shift. It involves fundamentally rethinking business models, processes, and customer experiences, fueled by a comprehensive adoption of digital technologies throughout the organization. Artificial intelligence and machine learning can be harnessed for demand forecasting, predictive analytics can optimize resource allocation, and IoT devices can enable real-time monitoring of supply chains. Moreover, businesses can personalize customer experiences through data-driven insights, leading to improved customer loyalty and market competitiveness (Walter et al., 2017). Digital transformation empowers food companies to innovate, seize new opportunities, and shape the future of the industry in an increasingly digitalized and data-driven landscape.

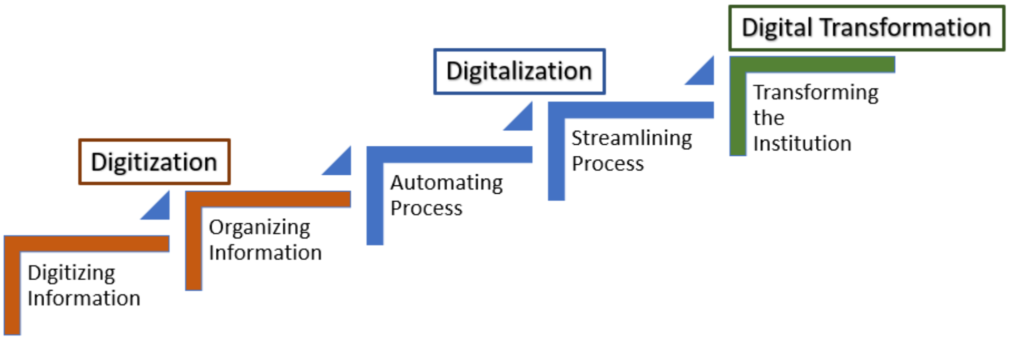

Figure 1 Three steps of digital revolutions

3. Artificial Intelligence (AI)

According to Andersen et al. (2018), AI systems have the capability to emulate human intelligence through various means, such as learning, sensing, providing explanations, and taking action. Industrial AI is a type of AI that is used for clearly defined and specialized tasks. It is sometimes referred to as weak or narrow application AI. These AI systems are designed to perform specific functions such as image recognition, language processing, or predictive analytics. In general, industrial AI systems incorporate one or multiple external data streams, sensors, and machine learning algorithms, alongside causal or logical constraints (Smith, 2018). Conversely, strong AI refers to a form of artificial intelligence that closely emulates human intelligence. Achieving strong AI remains an aspiration in the field of AI development, as it has not been realized thus far. Strong AI systems would be capable of human-like reasoning, problem-solving, and decision-making. Industrial AI systems convert data and predictions into actions and explanations, and they are used in industrial settings to provide decision support, detect abnormalities, automatically adjust processes, and analyze the root cause of problems (Zhou et al., 2019). For example, an industrial AI system could be used to analyze data from sensors on a manufacturing line to detect anomalies or predict when maintenance is required. The system could then take action, such as alerting maintenance staff or adjusting the production process to prevent further issues.

4. Machine Learning (ML)

Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on creating algorithms and models that enable computers to learn and improve from experience without being explicitly programmed. The core idea behind ML is to develop systems that can automatically identify patterns and relationships in data and make accurate predictions or decisions based on that knowledge. The learning process involves feeding large amounts of data into the algorithm, which then analyzes and processes the data to identify underlying patterns and structures (Jordan & Mitchell, 2015). Through this process, the ML model learns to recognize complex patterns, make decisions, and generalize from the data it has seen. The model's ability to generalize is essential, as it allows it to perform accurately on new, unseen data (Ahani et al., 2019). Artificial Neutral Network (ANN), Support Vector Machines (SVM), linear regression, and Q-learning are examples of ML.

4.1 Artificial Neutral Network (ANN)

Artificial Neural Network (ANN) are a type of machine learning model that falls under the category of supervised learning. ANNs are inspired by the structure and functioning of biological neural networks. They are composed of interconnected nodes, or artificial neurons, organized in layers. (Arel et al., 2010). The primary objective of ANNs involves the development of mathematical algorithms that enable them to learn by imitating the information processing and knowledge acquisition mechanisms observed in the human brain (Basheer & Hajmeer, 2000). ANNs are widely used for tasks like classification, regression, pattern recognition, and function approximation. In an ANN, artificial neurons, also known as nodes or units, are organized in layers. The typical architecture consists of an input layer, one or more hidden layers, and an output layer. Each neuron in a layer is connected to neurons in the adjacent layers through weighted connections. These connections enable information flow and learning within the network (Marquez, Herrera, Ojeda, & Maza, 2009).

4.2 Support Vector Machines (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression tasks. In SVM, the algorithm aims to find an optimal hyperplane that best separates or fits the data into different classes or predicts continuous values (Du & Sun, 2004). The hyperplane is chosen in a way that maximizes the margin between the two classes or fits the data points within a specified tolerance. One of the variant of SVM is Support Vector Regression (SVR). While SVM is primarily used for classification, SVR is designed to predict continuous numeric values instead of discrete classes. SVR is especially useful in scenarios where the relationship between the input features and the target variable is not linear and exhibits complex patterns (Astiningrum et al., 2021).

5. Fuzzy Logic (FL)

Fuzzy logic (FL) is a branch of mathematics and a type of multi-valued logic that allows for the representation and processing of uncertain or imprecise information. FL is often used in decision-making, control systems, and expert systems, where handling imprecise data or uncertainty is crucial. It is used to model and process human reasoning and subjective evaluations in various fields, including engineering, control systems, robotics, artificial intelligence, natural language processing, and more (De Pilli, 2022). FL provides a flexible and powerful framework for dealing with uncertain and imprecise information, allowing for more natural and human-like reasoning and decision-making. The primary advantage lies in its ability to closely emulate the decision-making logic of human control systems. This approach finds versatile applications across various systems, ranging from small, portable devices to extensive computerized process control systems (Huang et al., 2010). Fuzzy modeling employs imprecise yet highly descriptive language akin to human operators, enabling it to adeptly handle input data with a nuanced and context-aware approach. It has found applications in various domains, such as control systems, pattern recognition, risk assessment, medical diagnosis, and many more, where handling fuzzy or subjective data is essential.

6. Big Data

At the outset, big data was defined based on volume, variety, and velocity. These 3V’s dimensions encompassed the notion of copious amounts of unstructured data being generated rapidly and in diverse formats. Conventional software proved inadequate in handling such data, prompting the necessity for big data technology to effectively manage and process it (Misra et al., 2020). The manufacturing process, spanning from the acquisition of raw materials to the delivery of final goods, is anticipated to generate an immense volume of data, commonly referred to as big data. Big data analytics entails the examination and interpretation of extensive and diverse datasets to extract valuable insights and knowledge. The analytics process is used to uncover hidden patterns, unknown correlations, customer preferences, and market trends that can provide valuable insights for making well-informed business decisions. Big data analytics can provide valuable insights to manufacturers on how to optimize their operations, improve product quality, and reduce costs (Galanakis, 2021).

7. Internet of Things (IoT)

The Internet of Things is a contemporary manufacturing concept and fundamental technologies in Industry 4.0. It encompasses a sophisticated information technology infrastructure designed to collect and transmit data, exerting a substantial influence on the productivity and efficiency of production systems (Ben-Daya et al., 2020). The objective is to eradicate food insufficiencies and guarantee the accessibility of nourishing sustenance to all, transcending any economic, social, or environmental constraints. Moreover, in the food supply chain, the utilization of internet of things technology has demonstrated numerous benefits, as it is capable of facilitating the seamless coordination and management of all stakeholders across various stages of the supply chain. Additionally, IoT has the potential to overcome challenges related to traceability, visibility, and controllability. It also provides safety and sustainability in supply chain. In general, the advantages of IoT are provide real-time information on every actor of supply chain, easy monitoring, save money and time, and also provide transparency, visibility, safety, and sustainability to consumer hence for increasing consumer trusts (Galanakis, 2021).

The implementation of IoT technology has revolutionized the production process by facilitating the acquisition and distribution of real-time data to various resources such as jobs, materials, equipment, and personnel (Bi et al., 2014). In order to collect real-time data, radio frequency identification (RFID), sensors, and wireless communication technologies are commonly utilized (Lu et al., 2006; Zhong et al., 2013). The integration of these technologies enables the tracking and monitoring of critical information such as the movement of goods, personnel, and other relevant manufacturing operations in real-time, thus providing full traceability and visibility of the production process. This live data provides management with the ability to make faster and more informed decisions, ultimately improving the overall efficacy and efficiency of production operations.

8. Blockchain

Blockchain technology has emerged as a promising solution for secure and transparent record-keeping of digital transactions, eliminating the need for a trusted intermediary. The system utilizes various software protocols and algorithms to manage blocks of financial transaction data, enabling seamless transmission, processing, storage, and a user-friendly presentation of information. The original configuration of blockchain, as seen in bitcoin, consists of a timestamped header, transaction details, and a link to the previous block. Each block in the blockchain is uniquely identified by a hash code generated based on its contents, ensuring the integrity and immutability of transaction records. The decentralized and immutable characteristics of blockchain technology have rendered it suitable for a wide range of applications, spanning from financial transactions to supply chain management and data sharing (Sander et al., 2018). The hash code acts as a link between blocks, establishing a linked list structure where each block references the hash of the previous block. As a result, any alteration made to a particular block will cause a hash discrepancy with all subsequent blocks. The level of immutability in a blockchain depends on the difficulty of altering the transaction history. Private blockchains follow a slightly different process for adding blocks, where the legitimacy and recognition of the blockchain rely on the signature of a predetermined number of participants, instead of the costly Proof-of-Work method. This means that reconstructing the chain would require knowledge of the private keys of the other participants who added blocks (Tasca & Tessone, 2017).

Furthermore, data is stored in a decentralized manner, whereby data is not limited to a solitary server. Instead, the data is replicated across various computers, allowing all participants to access and examine multiple copies. Blockchain technology establishes a remarkably transparent environment where trust becomes unnecessary, and the involvement of a central authority to facilitate interactions between parties is obviated (Galanakis, 2021).

9. Deep Learning (DL)

Deep learning is a subfield of machine learning and artificial intelligence (AI) that focuses on creating and training artificial neural networks with multiple layers, known as deep neural networks. These networks are designed to learn hierarchical representations of data, allowing them to handle complex patterns and extract high-level features from raw inputs. The term "deep" in deep learning refers to the depth of the neural network, which involves stacking multiple layers of neurons on top of each other. Each layer learns to detect specific features or patterns at different levels of abstraction, passing the processed information to the next layer. The final layer, known as the output layer, produces the desired predictions or classifications based on the learned features (Zhou et al., 2019).

10. Application in the food industry

10.1 Post harvest

Image processing technologies and sensors offer significant potential for improving quality control and assurance measures in postharvest products. For example, artificial intelligence (AI) can be employed to automate tea grading by analyzing the tea's edge, resulting in more accurate classification compared to traditional methods (Jiang & Chen, 2021). Likewise, the maturity of watermelons can be evaluated by employing an acoustic impulse and an ANN linear model. In a separate investigation, Support Vector Regression (SVR) was employed to evaluate the quality of bananas, primarily focusing on color. Interestingly, SVR outperformed ANN in accurately predicting quality throughout the storage period (Sanaeifar et al., 2016). Fuzzy logic (FL) has found application in automating the storage of potatoes, fruits, and cassava roots within dedicated facilities to enhance postharvest quality control. (Sahni et al., 2021).

Deep Learning (DL) techniques have also been employed in the automatic sorting of bananas. The study utilized a deep learning-based RESNET-50 network to classify bananas as healthy or unhealthy, achieving an impressive accuracy rate of up to 90% (Helwan et al., 2021). In a study by Apolo-Apolo et al. (2020), DL was used to estimate citrus yield, employing the Faster R-CNN model to detect, count, and measure the size of citrus fruits, and establishing a network based on LSTM to estimate the overall citrus yield. The findings indicated that the proposed model demonstrated a remarkably low average standard error (SE) of only 6.59% when compared with manual counting results. Additionally, the estimated yields per tree exhibited a mean SE of 4.53% and a standard deviation (SD) of 0.97 kg when compared with the actual yields. Wang et al. (2018) in their study, focused on investigating the concealed and internal mechanical damage present in blueberries. To achieve this, they employed deep-learning technology in conjunction with hyperspectral transmittance data. Specifically, the CNN model was constructed using the ResNet architecture.

Furthermore, an electronic nose was employed to detect fungal infection, specifically the presence of Aspergillus in grain mildew in Japonica rice, Jasmine brown rice, and fungal microorganisms associated with aroma deterioration during postharvest storage and drying. The application of advanced technologies like deep learning-based networks and electronic noses provides highly sensitive and efficient methods for rapidly detecting and classifying various agricultural products, thereby enhancing quality control measures, ensuring product safety, and enhancing consumer satisfaction (Kutyauripo et al., 2023)

The application of PEGS (Paper-based Electrical Gas Sensor) and electronic nose systems exemplifies how technology can be utilized within the food industry to uphold food safety and quality. PEGS, which stands for paper-based gas sensors, possesses the capability to detect noxious gases like ammonia and trimethylamine in fish products and meat (Barandun et al., 2019). This technology alerts consumers if food is safe to handle or consume, thereby reducing the risk of foodborne illness. Electrical gas sensors play a crucial role in the digital transformation of the food industry. As the industry embraces digital technologies to improve various processes, electrical gas sensors provide essential data for real-time monitoring, quality control, and safety assurance. As consumer demands for transparency and traceability increase, the food industry needs robust systems to track and monitor the production and distribution of food products. Electrical gas sensors can aid in this aspect by providing data on environmental conditions and gas emissions throughout the supply chain. This data can be stored in digital databases or blockchain platforms, ensuring the traceability and compliance of food products with safety standards and regulations (Barandun et al., 2019). On the other hand, electronic nose devices feature an array of electronic chemical sensors designed to detect complex odors. This technique has been successfully used for shelf-life research, quality control, innovation evaluation, process monitoring, and authenticity assessment in various food products (Matindoust et al., 2016).

10.2 Food safety and quality

Ensuring the safety of food is a vital component of safeguarding public health, encompassing various processes such as processing, hygienic storage, and management to prevent the spread of illnesses among the population. However, with the globalization of the food industry and the increasing complexity of trade, ensuring food safety and quality has become progressively challenging. To tackle these challenges, several technologies have been introduced to ensure food safety. Gupta & Rakesh (2018) designed an IoT system that can detect adulterants in food products, and it contains various sensors for detecting parameters such as humidity, temperature, oil, salt, color, metal, viscosity, and pH. This system can be used by different players in the food supply chain to detect food adulteration effectively. Similarly, Nirenjena et al. (2018) developed an IoT system that aimed at preventing defect and deprivation in food. It can be used to monitor specific food commodities and assess the quality of food. They used sensors such as moisture, temperature, and GPS locations to detect food degradation. Smiljkovikj & Gavrilovska (2014) created SmartWine, a cloud-based system designed to oversee the wine supply chain, optimize resource utilization, prevent diseases, and enhance quality.

The development of these IoT systems shows the increasing use of technology to ensure food safety and quality.

Shih & Wang (2016) proposed an Internet of Things (IoT) system with practical applications, featuring an architecture for real-time remote monitoring. Utilizing wireless sensors, the system measured temperature along the cold chain in food processing, encompassing food preparation and transportation. Jin et al. (2017) introduced a novel mobile sensitivity absorptiometer to monitor pesticide residues in agricultural fields. The system incorporated a photo detection front-end sensor and an on-board microcontroller, facilitating communication with 4G technology between smartphones, the cloud, and food safety specialists, while Bluetooth technology enabled communication with the on-field detector. Zhao et al. (2015) designed a system for pesticide residue detection in agricultural products, integrating biosensors, wireless transmission, and a detection device (single-chip microcomputer) with an information-sharing platform, yielding positive results from real samples. Beker et al. (2016) proposed an IoT solution within the food supply chain to enhance food safety and quality. Consumers and retailers can utilize smartphones to gather packaging information (e.g., ingredients, allergies, and nutrition values) and additional data, such as product quality, freshness, origin, and applied pesticides, allowing for improved logistics and predictive shelf-life analysis.

10.3 Food supply chain

IoT can be leveraged to increase the functioning of every actor within the food supply chain. This includes farms, food manufacture, food handling and processing, food loading, allocating, storing, and usage. One of the main challenges within the food supply chain is traceability, visibility, and transparency, as well as controllability issues. IoT can tackle these obstacles by offering instantaneous information that can be effortlessly transmitted via a wireless network. RFID technology is widely acknowledged as one of the most effective and economically viable options available IoT technologies for tracking food products in the food supply chain. By embedding RFID tags in food products, critical information related to transportation can be stored and retrieved, enabling real-time alerts to be sent throughout the supply chain in case of food safety issues or food recalls, leading to immediate isolation of affected products. Chen et al. (2018) introduced the concept of Cognitive Internet of Vehicle (CIoV), which harnesses physical and network data space mining to augment transportation safety and network security. This concept has the potential to enhance transportation efficiency and safety within the food supply chain. The successful deployment of a Vehicular Ad-Hoc Sensor Network (MovingNet), comprising numerous sensors installed in public transport facilities, has enabled the detection of counterfeit alcohol production (Ramesh & Das, 2011), demonstrating how IoT can enhance the safety and quality of food products during transportation. To monitor humidity and temperature inside refrigerator trucks and cargo identification and tracking location in real-time, Zhang et al. (2011) proposed an intelligent monitoring system design based on IoT, including wireless communication technology, sensors, and RFID, which demonstrates how IoT can improve the efficiency and quality of food products during transportation and storage.

Chen (2015) proposed the use of radio frequency identification readers and tags to track products from the farm to the sales point stage in the supply chain. In another pilot IoT project conducted by Liu et al. (2016), RFID tags were employed to trace and monitor food within the supply chain, with data transmission facilitated through Wireless Sensor Network (WSN), Ethernet, and WiFi. Furthermore, a traceability platform tailored specifically for tilapia cultivated in aquaculture was developed by Yan et al. (2012). This platform utilized database server, Electronic Product Codes (EPC) technologies and radio frequency identification, EPC Information Service (EPCIS) server, and an Object Name Service (ONS). Similarly, Mededjel et al. (2017) devised an internet of things traceability system that employed RFID tags, a cloud platform, and electronic product codes to monitor and trace food products. The implementation of these technologies has facilitated efficient tracking and tracing of food products, simplifying the process of identifying the source of contamination or adulteration. As a result, food safety and quality assurance have been significantly improved.

In addition to IoT, blockchain technology can also be used to effectively enhance food supply chains by providing better traceability (Galvez et al., 2018). Blockchain is a scattered ledger technology that admits for the creation of a transparent and secure network of information sharing. Blockchain technology can be used in the food supply chain to detect and trace issues early by tracing back to their initial sources and players who may have been involved in fraud (Creydt & Fischer, 2019). Cargill Inc. and San Domenico roastery are two examples of food companies that employed blockchain technology to enable customers to track the origin of their products. This utilization of blockchain enhances transparency and provides reliable information about the turkeys sold by Cargill Inc. and the coffee products offered by San Domenico roastery (Bunge, 2017; Foodchain, 2019). The implementation of blockchain technology ensures that each stage of processing, from farm to store, is documented and finalized before proceeding to the next step. This transparent approach instills trust in customers, as they can rely on the information provided. Similarly, Downstream beer, a company in the beer industry, also adopted blockchain technology to increase transparency and authenticity. By recording each step of the brewing process, including ingredients used, on a blockchain, Downstream beer aims to provide customers with comprehensive information about their craft beer products (Ireland Craft Beers, 2017).

10.4 Food development and consumption

The food industry is highly competitive, and continuous new product development is crucial for companies to remain competitive. Recent research indicates that artificial intelligence (AI) can effectively mitigate the expenses linked to research and development (R&D) while concurrently improving the success rate of new product introductions. Moreover, the utilization of text mining techniques on social media platforms and online communities offers an automated means to identify consumer demands and generate novel product concepts (Kakatkar et al., 2020). Several studies have shown that using text mining algorithms to analyze social media and online communities can help companies identify emerging trends and consumer needs (Zhang et al., 2021). This information can be used to develop new products that are tailored to the needs and preferences of consumers, which can help increase the chances of success in the market. Moreover, some research has focused on using AI to generate process conditions and formulations that optimize expected quality properties such as shelf life, nutrition, and sensory properties (Zhang et al., 2019). This approach involves using a combination of mechanical models and machine learning to create an optimization structure that can consider various aspects such as government policies, supply, and sustainability. Using AI in the food industry can also help reduce R&D costs by automating some of the manual processes involved in developing new products. By analyzing data from previous product launches and using ML algorithms to identify patterns, companies can reduce the time and resources required to develop new products (Trinh et al., 2021). It can also help reduce the risk of product failure by identifying potential issues early in the development process. Besides AI and ML, the utilization of big data has the potential to assist decision-makers, farmers, and researchers in enhancing their comprehension, efficiently handling food supply and demand, anticipating food-related issues, and devising effective solutions to tackle food insecurity and price fluctuations. According to Nita (2015), the implementation of a big data-enabled system in a food manufacturing setting resulted in a significant forecasting accuracy of approximately 70% for the targeted commodities. This accurate forecasting offers several advantages, such as optimizing food chain operations, reducing product spoilage, efficiently planning, and utilizing resources, and ultimately enhancing the overall performance of the supply chain.

10.5 Food preparation

The field of food preparation has seen the development of sophisticated artificial intelligence (AI) algorithms and machine vision systems, which have enabled the monitoring of all cooking parameters and identification of fully cooked food based on its color. These systems can even stop the cooking process automatically to prevent overcooking. The food is categorized as overcooked, cooked, or uncooked and stirred by a robotic arm (Lin et al., 2021). Moreover, a proposal for a neural network and recommendation-integrated system that specializes in Thai cuisine has been suggested. This system not only takes into account the user's food preferences but also their health and eating habits to help them make informed food selection decisions. A food recommendation system has also been developed to provide nutrition-based food choices for diabetic patients (Samad et al., 2022). Furthermore, the application of natural language processing (NLP) techniques has facilitated the development of conversational chatbots capable of accepting orders through digital menu boards. AI techniques are being employed across diverse domains, including nutrition decision support tools, mobile apps, and telehealth platforms for remote nutrition assessments. While digital technology in the field of clinical nutrition is still in its early stages, there exists substantial potential for significant expansion (Limketkai et al., 2021).

10.6 Waste Management

The food supply chain operations are regarded as flawed due to the substantial resource requirements, including natural resources, water, and energy. Consequently, researchers and industry professionals have endeavored to establish sustainable FSC (Food Supply Chain) that achieve cost-effectiveness without compromising productivity. One technology that holds promise in this endeavor is the Internet of Things (IoT), which comprises interconnected devices capable of collecting and transmitting data. This data can be leveraged to minimize emissions and waste, aiding in the pursuit of sustainability (Rahimifard et al., 2017). Researchers have proposed a number of IoT-based solutions to improve the sustainability of food supply chains.

The IoT-based system was developed by Wang & Yue (2017) to prevent food waste and improve food safety at FSC. Hong et al. (2014) introduced a waste management system for food waste in Seoul that operates on the principles of the IoT. This system not only achieved a significant 33% reduction in waste but also led to worthy energy reserves of 16%. Jagtap & Rahimfard (2019) implemented a digital food tracing system using the internet of things in the prepared food industry, resulting in a 60.7% reduction in food waste. This reduction is achieved by identifying the sources of food waste, understanding the reasons behind them, collecting quality data, improving the system as a whole and influencing employee behavior.

Alpha-amylase production from banana peels was investigated using different modeling methods, Artificial Neural Network (ANN) and Central Convolutional Model (Bhat et al., 2010). This study found that ANN is more effective than Response Surface Method in predicting and optimizing alpha-amylase production. This shows that ANN is a powerful tool for predicting and optimizing complex biological processes, such as enzyme production. An IoT-based system has been developed to separate and classify household waste from dry waste based on moisture content (Das et al., 2021). This system has the potential to reduce landfill waste and improve waste management by separating waste that can be used for compost and other purposes. The prediction of bioethanol yield from watermelon waste was conducted using both Artificial Neural Network (ANN) and Adaptive Neuro-fuzzy systems. Bioethanol is generated through the fermentation of watermelon fruit waste utilizing *Saccharomyces cerevisiae*. (Jahanbakhshi & Salehi, 2019). The use of ANN and Adaptive Neuro-fuzzy inference systems allows accurate prediction of bioethanol yield, which has the potential to increase the profitability of bioethanol production from waste materials. In addition, the use of ANN, neuro-fuzzy adaptive systems and feedback methods were also investigated to predict the yield of biodiesel from vegetable waste (Amenaghawon et al., 2021). This study found that ANFIS has the highest accuracy of 99.3% in crop yield prediction, followed by ANN with 99.1%. This development and marketing can help improve the production of biodiesel and increase the use of vegetable waste as a renewable energy source.

10.7 Food Industry Operation

The food industry confronts numerous challenges in meeting consumer expectations regarding safety, health, and sustainable food. However, the integration of industrial robots, a key component of Industry 4.0, offers potential solutions to some of these challenges. By incorporating industrial robots, the industry can decrease production time and costs, enhance productivity and production capacity, and minimize manual labor and associated expenses (Duong et al., 2020). Plastic has already found applications in various sectors of the food industry, such as food processing. For instance, the Norwegian meat industry has embraced automation and multitasking by utilizing robots and food trucks for tasks like cutting and processing meat in slaughterhouses and meat factories. Increased automation in both primary and secondary meat production can significantly enhance productivity and capacity. (de Medeiros Esper et al., 2021).

In the food industry, another significant aspect of Industry 4.0 is the incorporation of sensors, including sensor-based technologies. Fingerprint technology, originally confined to laboratory equipment, has advanced into sensors and automated devices employed in intelligent factories as integral components of Food Industry 4.0. Current advancements in digital transformation technology have led to the creation of numerous exceptional sensor devices and platforms that are cost-effective and user-friendly (Kalinowska et al., 2021). These sensors are increasingly employed to oversee food safety, composition, food traceability and food quality, as well as to monitor performance and stability. Smart electronic sensors are also designed for food safety and quality. They can be used for process control, bringing food processing online and, in the case of smart devices, even integrating automation. These sensors have great potential to increase the efficiency and effectiveness of food safety and quality control measures (Mayer & Baeumner, 2019). Other examples of digital transformation applications in food industry can be found in Table 1.

Table 1 List of digital transformation application examples in food industry

Scope	Digital transformation application	References
Management and people	1. Smart talent acquisition 2. Talent online monitoring onboarding system 3. Talent development and training system (online system, using VR/AR technology) 4. Digitalization of personnel administration 5. Digitalization policy	Shufutinsky et al., 2020 Verma et al., 2020 Roldán et al., 2019 Bayraktar & Atac, 2018
Data life cycle	1. Data acquisition/collection from machine / activity 2. Data storage 3. Data analysis and presentation	Gorny & Wedel, 2022 Bersani et al., 2022
Product and service life cycle	1. Smart planning (forecast demand and supply, selling in and out) 2. Smart quality (integrated sensor in production line, auto rejector for non-conformity product, real time quality monitoring system) 3. Smart maintenance (predictive maintenance, spare part stock management and history system) 4. Smart process monitoring 5. Smart design product / service	Ammar et al., 2022 Bhatia & Ahanger, 2021 Chiu et al., 2017 Hassoun et al., 2022a
Technology	1. Data analytics integrated with dashboard real time monitoring system and push notification. 2. System integration from end to end 3. Decision support system	Islam & Dey, 2019 Konur et al., 2021
Factory operational	1. Smart warehouse in raw material, packaging material, spare part, supporting materials and finish good. 2. Smart production scheduling system 3. Collaborative robot and automated machine 4. Smart distribution tracking, traceability. 5. Smart assistance for repairing machines. 6. Customer feedback and relation system 7. Audit system and improvement follow up project or nonconformity system	Van Geest et al., 2021 Oluyisola et al., 2022 Goel & Gupta, 2020 Ali et al., 2021 Hassoun et al., 2022b Konstantinidis et al., 2020 Oltra-Mestre et l., 2020 Asif et al., 2020

11. Limitations and challenges

Digital transformation in the food industry encounters challenges in cost and investment, data privacy, and workforce adaptation. The implementation of new technologies requires significant upfront expenses, posing barriers for small and medium-sized businesses. Ensuring data privacy and cybersecurity becomes crucial when handling sensitive customer and supply chain information (Lehmann et al., 2012). Additionally, adapting the existing workforce to new technologies may encounter resistance and necessitate upskilling efforts. Interoperability among different digital systems, compliance with food industry regulations, and data overload are further hurdles. Integrating various platforms and software applications poses challenges, leading to inefficiencies and data inconsistencies. Adhering to food safety and quality regulations while implementing digital solutions can be complex. The vast amount of data generated through digital transformation requires advanced analytics capabilities to extract valuable insights (Demartini et al., 2018).

Consumer acceptance of digital technologies and infrastructure limitations are additional challenges. Some consumers may be hesitant to adopt new technologies or prefer traditional methods for food purchasing and consumption. In certain regions, especially rural areas, the lack of robust digital infrastructure and connectivity can hinder the seamless integration of digital solutions in the food supply chain (Jiang & Stylos, 2021). Ethical concerns arise with the use of emerging technologies like artificial intelligence and automation. Job displacement, algorithmic biases, and control over decision-making processes are ethical considerations that need attention (Bankins & Formosa, 2023). Moreover, over-reliance on technology may result in decreased human interaction and personalization, impacting customer relationships and loyalty.

Addressing these limitations demands careful planning, investment, collaboration, and ethical considerations. Companies need to strike a balance between leveraging technology's potential benefits while mitigating potential risks and ensuring a seamless transition for all stakeholders involved. Taking into account the diverse challenges posed by digital transformation in the food industry is crucial to its successful implementation and sustainable growth.

12. Conclusion

The application of digital transformation in the modern food industry is increasingly competitive and imperative due to the growing demand for safe, nutritious, and sustainably produced food. However, this potential is currently underutilized or ignored by many food industry stakeholders. This paper presents an overview of how the implementation of Industry 4.0 can enhance the sustainability and efficiency of the food supply chain (FSC). The food supply chain encompasses an intricate system that comprises various participants, such as farmers, food producers, providers, sellers, and customers. Incorporating technological advancements into all aspects of food supply chains can lead to better optimization and increased sustainability of the entire supply chain. For instance, IoT sensors can be used to monitor and control various food operational activities, such as temperature, humidity, and quality control. Moreover, big data analytics can be used to gather and analyze large amounts of data generated by the FSC. Machine learning algorithms can then be applied to the data to make predictions and optimize processes, such as predicting demand and optimizing inventory management. Finally, the use of AI can automate multiple functions within FSCs, such as quality control, traceability, and supply chain management.

13. References

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