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Advances of Digital Transformation Tools in Food Engineering Research: Process Simulation and Virtual Reality Applications in Production Processes

Ali Coşkun DALGIÇ[1*]

Keywords
Artificial Intelligence,
Digital Twin,
Process Simulation,
Virtual Reality,
Internet of Things

Abstract – The food industry, research and education, along with the development of technologies, are faced with very broad and complex application areas. In order to meet the nutritional needs and expectations of the growing world population and to ensure food quality and food safety expectations, there is an increasing need for computer applications in the control, modeling, optimization, and data analysis of production systems. In this context, digital transformation tools have a significant impact on food engineering research and education, as well as industrial applications. The aim of this study is to examine the role of digital transformation tools in food engineering, especially process simulation and virtual reality applications in production processes. Process simulation makes it possible to analyze (technical, economic, and environmental) various scenarios by creating mathematical models of production processes in a digital environment. When process simulations communicate with real-world production systems, digital twins are created. With this application, production efficiency increases, waste is reduced, and quality is improved. Virtual and augmented reality can be used in various areas, such as training, simulation, design, and inspection in production facilities. This technology allows users to simulate real-world scenarios and understand production processes more effectively. In the next part of the study, a framework is proposed for the integration of process simulation and virtual/augmented reality applications with other digital transformation tools. It is concluded that this framework will provide a powerful structure for optimizing and improving production processes in the food industry.

1. Introduction

Nowadays, research in the field of food engineering is becoming increasingly complex and researchers in this field are faced with many problems in the development of products, improvement of production processes, quality control, and ensuring food safety. Digital transformation tools have become an important tool in solving these problems. The use of digital transformation technologies in the food industry aims to increase efficiency and productivity, facilitate decision-making, increase profitability, develop innovative technologies and methods, and facilitate risk management (Konfo et al., 2023). There are various digital transformation tools used in the food industry at many stages, from agricultural production to end-user food safety. Artificial intelligence (AI), the Internet of Things (IoT), blockchain, digital twins, smart sensors, 3D printing, robots, big data, and virtual reality applications are among these tools (Nugroho et al., 2023) (Figure 1).

AI, process simulation, and IoT applications have a significant impact on food engineering research. AI, with its ability to analyze complex data and build predictive models, plays an important role in areas such as product formulation, nutrient composition optimization, and automation of production processes. AI comprises the technologies involved in electronic devices, computer systems, and robots, all designed to enhance and optimize the speed, precision, and effectiveness of user tasks (Esmaeily et al., 2024), (Thapa et al., 2023).

Process simulation is modeling and analyzing a process or system in a virtual environment to analyze, improve, and optimize the performance of an organization, business, or system. Digital twins, one of the digital transformation tools, are the creation of digital copies of real assets in the physical world. Digital replication is

[1]***Corresponding Author.** Gaziantep University, Engineering Faculty, Food Engineering Department, 27310 Gaziantep/Türkiye. E-mail: dalgic@gantep.edu.tr
OrcID: 0000-0001-6806-5917
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an important tool used to understand, control, and analyze the real world using process simulations (Koulouris et al., 2021). Process simulation supports decision-making processes in areas such as the design of production facilities, capacity planning, energy consumption optimization, and risk analysis. The evolution of these technologies in the field of food engineering has emerged as a reflection of the transformation in the industry (Saydam et al., 2020), (Dursun et al., 2020) and (Hassoun et al., 2022).

The IoT refers to a network of interconnected devices that can communicate and exchange data with each other over the internet without any physical intervention. Equipped with sensors, actuators, and connectivity features, these devices can collect data and transmit it to other devices or central systems, where it can be analyzed and acted upon. The majority of IoT applications in the food industry focus on monitoring temperature, traceability, humidity, color and enhancing sustainability performance (Konfo et al., 2023), (Hassoun et al., 2022).

Virtual and augmented realities are worlds created by digital technologies in virtual environments. Virtual reality (VR) creates fully digital environments for users to interact with, while augmented reality (AR) enhances the user's perception of their surroundings by overlaying digital content on top of the real world. VR and AR technologies, with the latest technological developments; are becoming widespread in many areas, especially in medicine and production. There are also many applications in the fields of engineering, education, automotive and tourism. VR and AR technologies in industrial manufacturing, from initial product design and assembly to real-time discussions between multidisciplinary teams around the world, provide fewer design errors throughout the production process, improved business solutions and longer effective working times (Crofton et al., 2019).

This comprehensive study aims to investigate the advantages and current potentials of contemporary technologies such as AI, VR, process simulation, and IoT by examining topics that are a combination of them. This study will also discuss a framework working model that includes the basic principles of these technologies, their use, and their integration with each other.

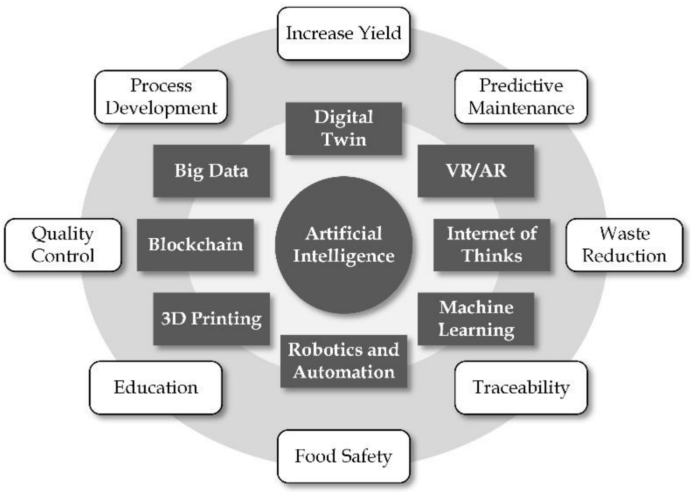

Figure 1. Digital transformation tools and applications in food engineering.

2. Digital Transformation Tools in Food Engineering

2.1. Artificial Intelligence

According to Haenlein et al. (2019), AI is defined as the ability of a system to comprehensively comprehend external data, learn from that data and use that learning in the applications that need it. Therefore, AI takes data from many sources (the IoT, big data sources, and expert systems) and uses knowledge-based rules or machine learning-based patterns to achieve predetermined goals. AI tools can also be classified as machine learning tools, natural language processing tools and image processing tools.

AI applications in the field of food engineering include sensory technology, computer vision systems (CVS), artificial neural networks (ANN) and fuzzy logic (FL) applications (J. Chen et al., 2020) (Table 1). The application of sensor technology is of great significance to AI. Dozens of studies exist that combine various types of sensors and food processing technologies to control key process parameters such as temperature during the drying of fruits and vegetables and pH levels for fermentation (J. Chen et al., 2020). Computer vision is one of the earliest AI technologies applied in food processes and used to measure parameters of physical properties such as size, shape, texture, color and quality of the products in real time (Kakani et al., 2023).

CVSs include tools such as machine learning, graphics, three-dimensional visuals, virtual reality, and augmented reality. There are many studies on this subject. In the review study by J. Chen et al. (2020), CVS applications in food drying systems are included. Among the image processing studies, CVS applications were performed in banana (Jiang et al., 2015), apple (Aghilinategh et al., 2016) and kiwifruit drying processes (Nadian et al., 2016).

ANN, another AI tool, consists of interconnected nodes, or artificial neurons, arranged in layers. Information is processed through the network by propagating signals from input neurons to output neurons through hidden layers. In the ANN, patterns and relationships in these data are first trained using algorithms, and then classification, regression, pattern recognition, and more applications are performed through the network (Barthwal et al., 2024). In many studies, ANNs have been used to modeling and optimization of food processes. Among these studies, ANNs were used in the drying processes of carrot (Erenturk and Erenturk, 2007), banana (Taheri et al., 2018), tomato (Abioye et al., 2024), and green peas (Barzegar et al., 2015) and in the optimization of extraction processes in soursoap fruit (Mahesh et al., 2024).

Fuzzy logic is a field of AI and computing used to address problems related to uncertainty. Unlike systems that work with traditional logic, this method recognizes uncertainty rather than relying on precise truth values (Atthajariyakul and Atthajariyakul, 2006), (Dash et al., 2024), (Li et al., 2021) and (Yousefi-Darani et al., 2019).

Table 1. Application of artificial intelligence in food processing

Products	Aims	AI methods	Food Processing	References
Carrot	Mathematical models drying process	ANN	Drying	Erenturk and Erenturk, 2007
Paddy	Optimum drying process conditions	FL	Fluidized bed drying	Atthajariyakul and Atthajariyakul, 2006
Banana	Process model	ANN	Hot air drying	Taheri et al., 2018
Mushrooms	Simulation and optimization of drying process	Genetic algorithm	Drying	Rahman et al., 2014
Banana	Drying uniformity analysis	CVS	Microwave-freeze drying	Jiang et al., 2015
Green peas	Quality optimization	ANN	Hot air infrared-assisted vibratory bed dryer	Barzegar et al., 2015
Apple	Image processing	CVS	Microwave convective drying	Aghilinategh et al., 2016
Kiwifruit	Improvement of kiwifruit drying	CVS	Hybrid hot air-infrared drying	Nadian et al., 2016
Tomato	Modelling of quality attributes	ANN	Convective hot-air drying	Abioye et al., 2024
Soursop fruit	Optimization of extraction techniques	ANN	Solvent extraction	Mahesh et al., 2024
Chili pepper	Improvement of classification method of peppers	ANN	Classification	Cruz et al., 2021
Rice pancake	Rheology and sensory evaluation	FL	Statistical analysis of rheological properties	Dash et al., 2024
Hawthorn	Control of relative humidity	FL	Microwave drying	Li et al., 2021
Dough	Process control	FL	Dough proofing	Yousefi-Darani et al., 2019

2.2. Digital Twins

The concept of a digital twin is a conceptual integrity created using real-world data needed by a simulation created to analyze a system or process (Y. Chen et al., 2020). According to Kritzinger et al. (2018), digital system integration between the physical and digital systems is classified as a digital model, a digital shadow, and a digital twin. A digital model is a digital representation of a physical system without automatic data exchange. A digital shadow is a union in which there is a one-way data flow from the physical system to the digital system created in the digital environment. In the concept of the digital twin, there is a unity including mutual automated data flow between the physical and digital systems (Kritzinger et al., 2018). The actual data transfer between the virtual and real systems is performed by synchronizing and simulating the data obtained from smart devices connected to the physical system through mathematical models.

Process simulation involves using computer-based models to analyze, predict, and optimize the behavior of industrial processes. It entails creating a digital representation of a real-world process, often with specialized software, to simulate how it behaves under different conditions. Process simulators enable mass and energy balances to be realized, equipment specifications to be determined, workforce needs to be estimated, profitability and sensitivity analyses to be made by economic evaluations, and environmental impacts to be investigated with virtual models of production processes created in a computer environment (Koulouris et al., 2021).

There are studies involving digital twins and model studies where high-value-added products are obtained from different food industry wastes (Table 2). The main ones of these wastes are sugar beet/cane molasses (Saydam et al., 2020), (Munagala et al., 2021), (Rathnayake et al., 2018), grain product wastes (Saydam et al., 2020), (Dasgupta et al., 2021), (Koulouris et al., 2021), vegetable oil production wastes (Donaldson et al., 2012), (Innocenzi and Prisciandaro, 2021), (Mabrouki et al., 2015), (Sayar et al., 2018), (Yun et al., 2013), and fruit and vegetable wastes (Lohrasbi et al., 2010), (Martínez-Ruano et al., 2018). Many of these studies involve biotechnological processes and mainly organic acids have been produced (Munagala et al., 2021), (Sayar et al., 2018). These organic acids (lactic acid and acetic acid) have higher economic values than the raw materials used in their production. In addition to organic acids, there are also simulation studies involving pigments (Dursun et al., 2020) and additives. There are also simulation studies involving the production of energy crops such as ethanol (Unrean and Khajeeram, 2016), (Rathnayake et al., 2018), biofuels (Mabrouki et al., 2015), biodiesel (Innocenzi and Prisciandaro, 2021), (Mabrouki et al., 2015), hydrogen gas (Han et al., 2016), and biogas (Mel et al., 2015), (Martínez-Ruano et al., 2018). In Karadeniz et al.'s study, the virtual and physical environment of the ice cream production machine is controlled by the digital twin concept (Karadeniz et al., 2019).

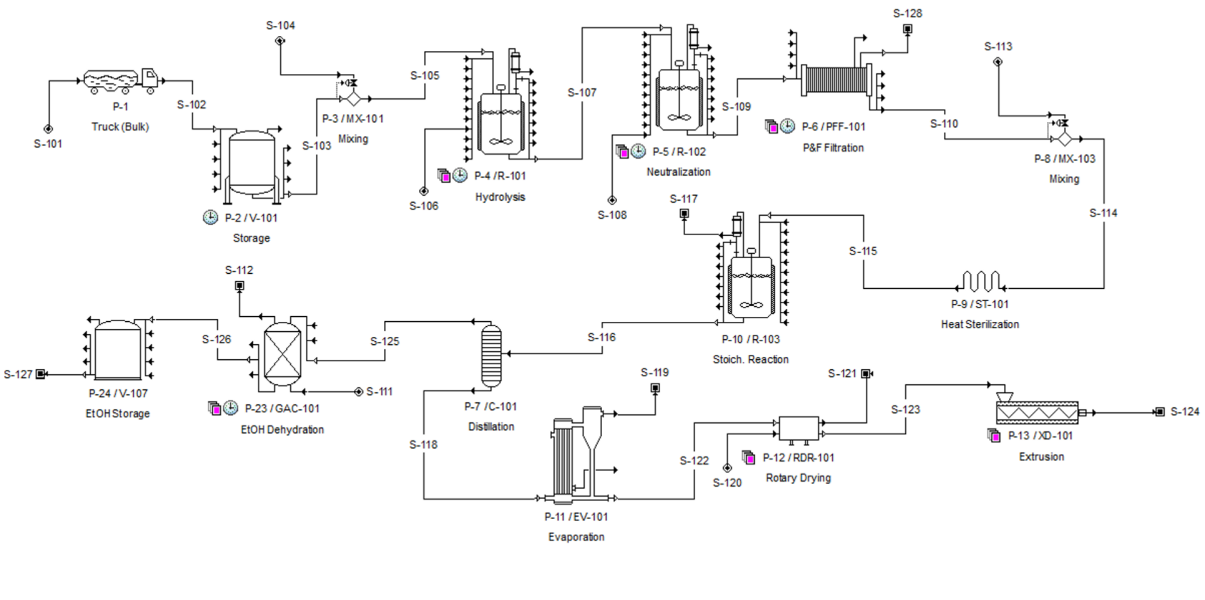

Figure 2. A digital model created by Superpro Designer for the production of bioethanol from sugar beet molasses (Dalgıç, 2018)

In process simulation, analyses can be performed from a single-stage process to a multi-stage process. It enables economic analysis (investment costs, operating costs, and profitability), work-time graphs, mass-energy balances, and sensitivity and uncertainty analysis in batch or continuous systems (Saydam et al., 2020), (Lohrasbi et al., 2010), (Mel et al., 2015), (Martínez-Ruano et al., 2018) and (Sayar et al., 2018). Environmental impact analyses are also performed using mass and energy balances (Dasgupta et al., 2021), (Martínez-Ruano et al., 2018), (Munagala et al., 2021) and (Rathnayake et al., 2018). The process is optimized technically and economically by changing production parameters (capacity, technology, input material characteristics, and economic data) (Saydam et al., 2020), (Unrean and Khajeeram, 2016) and (Yun et al., 2013).

Figure 2 illustrates the digital model for producing bioethanol from sugar beet molasses. This study encompasses alcohol purification following fermentation as well as the drying process for the distillation by-product (shillempe) (Dalgıç, 2018).

Table 2. Application of digital twins and models in food processing

Raw Material	Products	Food Processing	Analysis	DT/DM	References
Sugar beet molasses	Xanthan and sorbitol	Bioprocessing	Techno economic	DM	Saydam et al., 2020
Sugarcane bagasse	Lactic acid	Bioprocessing	Life cycle and economic assessment	DM	Munagala et al., 2021
Cotton stalk	Acetic acid	Bioprocessing	Retro-techno-economic evaluation	DM	Sayar et al., 2018
Agro-industrial wastes	Astaxanthin	Bioprocessing	Techno economic analysis	DM	Dursun et al., 2020
Sunflower seed	Energy and activated carbon	Chemical reaction	Process simulation	DM	Donaldson et al., 2012
Sugar cane bagasses	Ethanol	Fermentation	Optimization and techno-economic assessment	DM	Unrean and Khajeeram, 2016
Citrus waste	Limonene	Extraction	Process design and economic analysis	DM	Lohrasbi et al., 2010
Agricultural biomass	Biogas	Anaerobic digestion	Economic analysis	DM	Mel et al., 2015
Banana peel	Biogas	Anaerobic digestion	Techno- economic and environmental assessment	DM	Martínez-Ruano et al., 2018
Virgin oil and waste cooking oil	Biodiesel	Bioconversion	Technical feasibility	DM	Innocenzi and Prisciandaro, 2021
Palm oil residues	Biofuel	Pyrolysis	Process simulation	DM	Mabrouki et al., 2015
Waste cooking oil	Biodiesel	Bioconversion	Process simulation and energy optimization	DM	Yun et al., 2013
Cassava, cane molasses, and rice straw	Bioethanol	Fermentation	Life cycle assessment	DM	Rathnayake et al., 2018
Corncob	Xylitol	Bioconversion	Energy and life cycle impact assessment	DM	Dasgupta et al., 2021
Food waste	Hydrogen	Bioprocessing	Techno-economic evaluation	DM	Han et al., 2016
Malt	Beer	Fermentation	Production simulation and scheduling	DT	Koulouris et al., 2021
Milk	Ice cream	Ice Cream Machines	Process control	DT	Karadeniz et al., 2019

2.3. Internet of Things

The IoT refers to a network of physical objects or "things" embedded with sensors, software, and other technologies that enable them to communicate and exchange data with other devices and systems over the Internet. The IoT system consists of devices, network structure, software, and security. IoT system devices include all devices implemented in the environment and communication gateways, sensors (e.g., temperature, light, motion, location, etc.), devices that transmit and receive information (e.g., receivers and transmitters), energy supply devices (e.g., batteries, solar panels), and gateways that can manage functions. Devices also include all relevant communication technologies, both wired and wireless, such as Wi-Fi and Bluetooth (Bouzembrak et al., 2019), (Verdouw et al., 2016). The use of IoT in food supply chains has been identified as one of the application areas in food production, processing, storage, distribution, consumption, traceability, visibility, and controllability challenges.

2.4. Virtual and Augmented Reality

VR is defined as a computer-generated digital environment created as if it were real. AR improves the user's perception and interaction with the environment by superimposing digital content on the real world. The main purpose of VR technology is to involve the user in actually experiencing the stimulated environment, and at the same time, the user will use one or more senses to feel like they are in the real world. AR is a field of research that deals with the combination of real-world and computer-generated data. AR is a technology that enables virtual objects to be placed in the real world in real time. The main difference between VR and AR is that VR technology is based on virtual information, while AR technology uses the real environment with additional computer-generated information (Figure 3) (Carrasco and Chen, 2021), (Crofton et al., 2019). Table 3 represents the application of virtual and augmented reality in food processing.

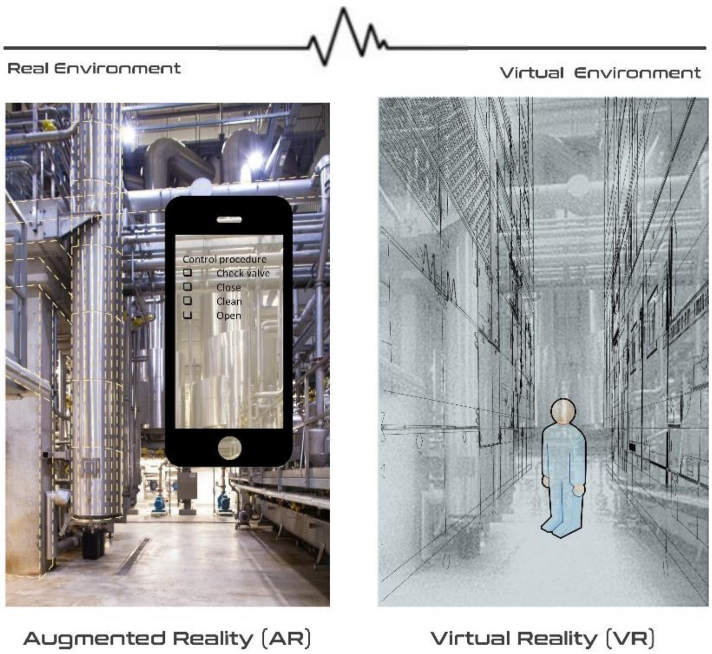

Figure 3. Virtual and real environment difference between VR and AR

2.4.1. Sensory Evaluations

Sensory evaluation is a scientific field that analyzes and measures human responses to the composition and nature of food and drink. It focuses on how we perceive and react to various stimuli using our five senses: sight, smell, touch, taste, and hearing. VR and AR technologies have the potential to revolutionize the way we collect and analyze sensory and consumer data. It is accepted in many studies that consumers' sensory responses are related to the condition of the environments in which food is consumed. It is also stated in many studies that the positive results in laboratories where food products are sensorial analyzed are different from the consumption habits in the real environment. Although there are many factors that may affect these results, one of the main reasons is that sensory analysis laboratories do not represent the real environment (Crofton et al., 2019), (Xu et al., 2021). Some of the sensory analysis studies that created real environment perception using VR and AR include chocolate (Van der Waal et al., 2021), snack foods (Pennanen et al. 2020), fruit juice and cake (Ammann et al., 2020), pastry (Alba-Martínez et al., 2022), and yogurt (Dong et al., 2021).

2.4.2. Food Quality and Safety

Real-time quality assurance and inspection play crucial roles in the food industry, guaranteeing that products adhere to the necessary safety and quality standards. AR technology is now being widely utilized in this field to transform inspection procedures, elevating the accuracy and efficiency of quality control. AR integrates with quality control activities, enabling online data transfer to auditors and the quality control team. These capabilities empower the food industry to continually improve quality standards, reduce waste, make more efficient use of labor, and minimize risks (Liberty et al., 2024).

2.4.3. Food Process Design

It is becoming increasingly difficult for food engineering students to visit large-scale facilities for process and plant design studies. This situation becomes even more difficult to access when the strict measures in occupational health and safety practices are taken into consideration. Apart from educational activities, it may not be possible for any investor to visit a facility in industrial applications in a competitive environment. Virtual reality applications open up opportunities for innovative approaches to provide simulated environments in higher education and in the design phase of industrial investment research (Hungler et al., 2022).

2.4.4. Food Traceability

Traceability, which is one of the most important applications in food safety, enables consumers to access healthy data about the food they consume. Consumers want to access healthy information about where the product they buy comes from and in which process steps it passes. Augmented reality applications offer a powerful interface to access digital information on this subject (Todorović et al., 2019).

Table 3. Application of virtual and augmented reality in food processing

Topics	Applications	VR/AR	References
Sensory evaluation	A research on psychological and physiological effects of chocolate in virtual reality environment	VR	Van der Waal et al., 2021
	Effect of virtual eating environment on consumers' evaluations of healthy and unhealthy snacks	VR	Pennanen et al., 2020
	Color evaluations of fruit juice and cake samples	VR	Ammann et al., 2020
	Investigation the effects of AR environments on the sensory responses of consumers towards different yogurts	AR	Dong et al., 2021
Product development	Product development and visual evaluation of pastry	VR	Alba-Martínez et al., 2022
Process design	Chemical plant design and development	VR	Hungler et al., 2022
Traceability	Food packaging	AR	Todorović et al., 2019

2.5. Blockchain in Food Processing

In food supply chains, ensuring accurate and timely information flow between producers, consumers, and regulatory authorities is an important prerequisite for minimizing food safety problems. Blockchain technology provides transparency in accessing product information within traceability systems. Information at all stages of production, from farm to fork, is recorded. In this case, health risks are reduced and fraud is prevented by eliminating production fraud (Islam and Cullen, 2021).

"Blockchain technology is a database that can be created in an electronic spreadsheet in a short time. The most important feature of these databases is that the information can only be added. Another feature is that each entry in the database (called a block) is cryptographically linked to the last entry" (Yuan and Zhou, 2023).

In the review study many hypotheses were proposed, and these hypotheses were supported by literature studies. One of the proposed hypotheses is that a blockchain-based food traceability system increases consumers' perceptions of product quality and safety, thus increasing their confidence in the product and increasing their willingness to purchase (Tao and Chao, 2024).

Successful traceability implementation requires collaboration and adoption across the entire supply chain, as well as addressing challenges such as interoperability, data privacy, and scalability.

3. Integration of Digital Transformation Tools

Based on the information gathered in the introduction to this review, a framework for how digital transformation tools can be used in food production systems, research, and educational tools is proposed. Figure 4 shows the framework for the integration of digital transformation tools. Each of the digital transformation tools contributes to achieving its goal with many different applications in order to increase efficiency, utilize limited resources, increase profitability, and reduce the environmental impacts of production systems. Therefore, it is imperative that all these tools be used effectively and efficiently.

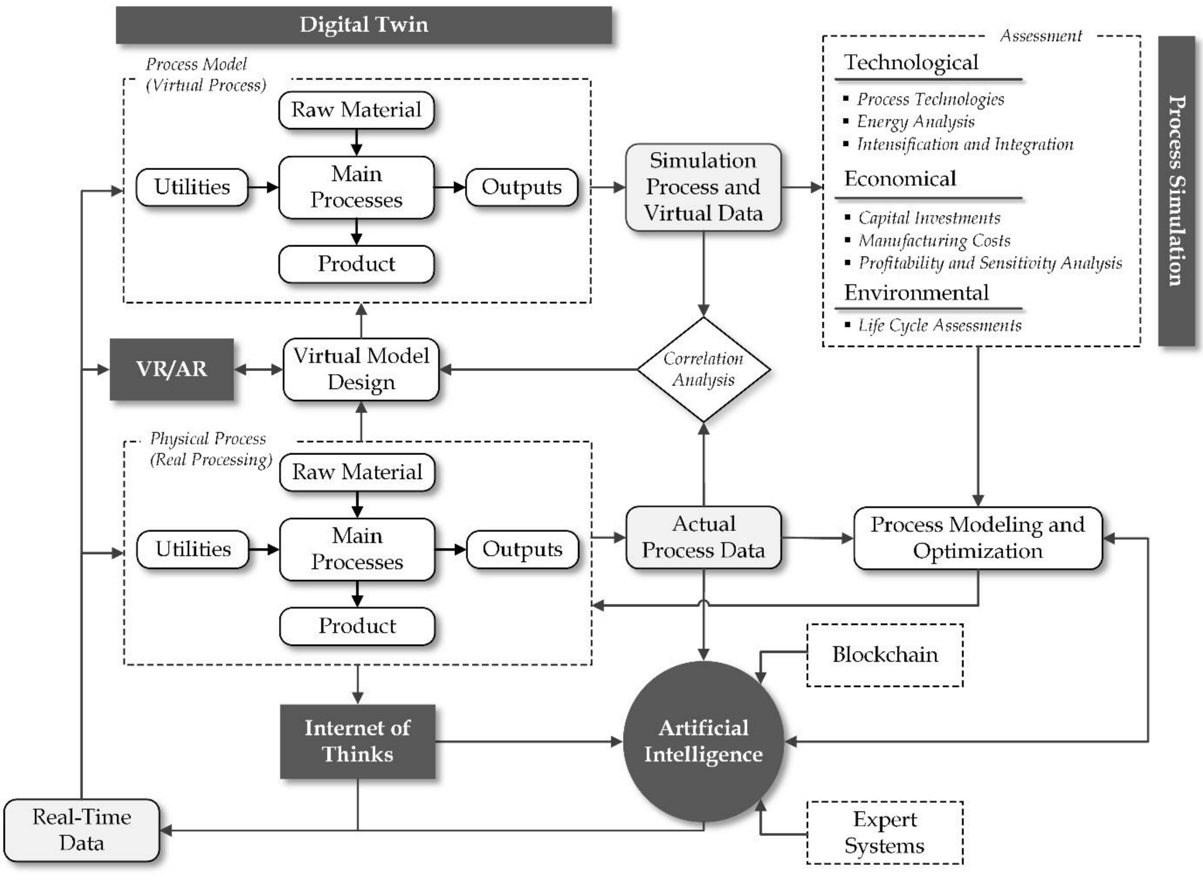

Figure 4. The frame work of the integration of digital transformation tools in food engineering

If we think of production systems as a two-stage system, design and production, we can use process simulations as a feasibility tool at the beginning. Likewise, when we consider VR technologies as a design tool, we can perceptually and technically analyze the production system in a healthier way before implementing it. Other tools can also be utilized during the design phase. AI is, of course, a great support tool for analyzing the designed processes.

In the evaluation of a production stage or equipment that has been digitally modeled in the design phase, many digital analyses are performed. These analyses can be classified as technical, economic, and environmental. As a result of these analyses, decision-making processes on issues such as other investment instruments and legal regulations come into play in the realization of the investment. In the production phase, a connection is created between the physical production and the digital model. This connection can be for data transfer only, or the data transfer between the digital process and the physical process can be for the control of the physical system. This is known as a digital twin. As a result of the evaluation of physical and digital production, the system efficiency is determined by the difference between theoretical and actual. The data generated within the system can be evaluated online. In this case, the IoT is a great help. For the non-system data that the system needs, blockchain, AI, and expert systems can be integrated into the system. AI tools can also be used in the control, monitoring, modeling, analysis, and optimization of the system. The integrated use of process simulations, AI, blockchain, VR/AR, and the IoT has many advantages, including dynamic simulation, optimization, real-time control, predictive maintenance, validation, and calibration of food processes.

4. Potential Challenges and Future Trends in the Food Industry

The application of digital transformation tools in the food industry brings many benefits, such as increased productivity and profitability, but also many implementation challenges. Factors such as high implementation costs in the start-up phase, data security and privacy concerns, the complexity of the supply chain from raw materials to the final product, and the old network structures of small businesses pose obstacles for businesses with limited budgets. In addition, the conservatism of employees in enterprises due to concerns about job loss and the lack of sufficient information infrastructure are also obstacles to the implementation of digital transformation tools.

Addressing data security and privacy concerns; researching and discussing potential risks will facilitate the implementation of digital transformation tools. In addition, risk assessments in terms of cyber security will also be useful in terms of applications. Workforce concerns of employees can be addressed through appropriate and effective training programs for digital transformation tools.

Digital transformation tools are expected to revolutionize the food industry, driving innovation, increasing efficiency, improving product quality and safety, and ultimately meeting the evolving demands of consumers in a rapidly changing market environment. Mainly agricultural practices, food safety systems, innovation of new functional products, and supply chain management will be impacted by AI applications as digital transformation tools for the food industry in the future. The use of virtual and augmented reality applications in food production processes can help optimize training, maintenance and production processes. It is also expected that optimization of production processes, improvement of product quality, product and process design and traceability will become widespread with digital twin applications.

5. Conclusion

In this review, studies involving digital transformation tools in food engineering research, education, and industrial applications were evaluated. As a result of these evaluations, a framework for the integration of digital transformation tools was developed and important findings emerged:

- Digital models of industrial production processes are predominantly created in the studies, and studies on digital twins have just started in food production processes.
- In most of the digital model-process simulation studies, the parameters affecting the processes are evaluated technically, economically, and environmentally.
- The digital twin process can make a great contribution to food engineering studies in real-time control, optimization, data-driven simulation, and predictive maintenance. With the application of the Internet of Things, process simulations can be applied more quickly and efficiently in collecting and monitoring data.
- Virtual and augmented reality applications are mainly used in sensory analysis studies. There are very few food engineering education and process design applications.
- Blockchain applications are mainly involved in traceability studies in food production systems. It is thought that this application can be applied to a wider area regarding food safety.

As a result, it is thought that each of the digital transformation tools can be applied differently in food production processes, and higher-quality and healthier products can be produced in an environmentally friendly and economical way.

Ethics Permissions

This paper does not require ethics committee approval.

Conflict of Interest

Author declare that there is no conflict of interest for this paper.

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