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Digital Twin applications in the food industry: a review

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With the rapid growth of today's market, food processing industries are compelled to adopt advanced solutions to ensure product safety and quality, reduce costs amidst low-profit margins, guarantee timely delivery of an increased demand for product preferences, and enhance sustainability. To cope with these challenges, Digital Twin (DT) technology has emerged as a promising solution. Due to the relative novelty of this technology, research on its application within the food processing industry remains limited, necessitating additional studies to better understand its potential and multifaceted role from different perspectives. This review analyzes existing studies on DT applications in the food industry, discussing the concept, benefits, and challenges hindering its full adoption. On this basis, this study contributes to the existing body of knowledge on DT by identifying the state-of-the-art within the food processing industry and categorizing use cases from both industrial and academic contexts. Further, it explores the DT from a sustainability perspective, emphasizing its role in optimizing resource utilization for more efficient and sustainable food processing. Furthermore, the study examines its potential as a versatile tool to support sustainability initiatives within the industry. Lastly, it discusses the future impact of DT in shaping the evolution of food processing.

KEYWORDS

food processing industry, digital model, digital shadow, Digital Twin, simulation tools, industry 4.0, sustainability

1 Introduction

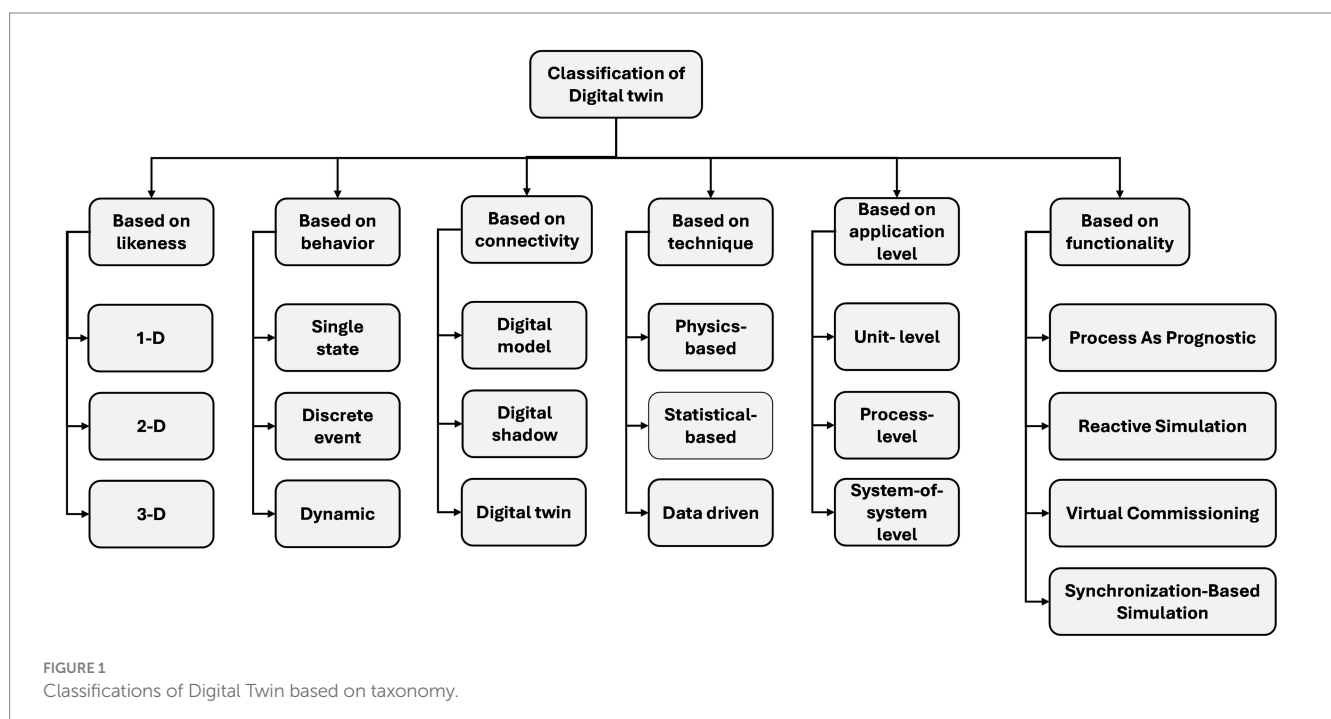
The food processing industry is inherently complex and diverse, encompassing various food types, processing methods, preservation techniques, and distribution systems. This complexity gives rise to numerous challenges, including increased consumer demands, product diversification, and sustainability concerns (Karadeniz et al., 2019; Maheshwari et al., 2023; Ciano et al., 2021; Verboven et al., 2020; Wari and Zhu, 2019). Therefore, the industry is compelled to rethink approaches to enhance productivity, efficiency, quality, and sustainability, as well as meet consumer demands. Small and medium-sized food processing industries typically adopt a non-integrated approach to process optimization, dictated by their priorities, resources, and data availability (Klemeš et al., 2008). Further, many still rely on traditional process design methods driven by vendor management systems using unstructured data analysis and demand prediction (Maheshwari et al., 2023; Wari and Zhu, 2019). These traditional methods prioritize products over customers, emphasizing profit maximization rather than customer satisfaction by implementing short-term goal-seeking strategies rather than long-term comprehension (Leng et al., 2020; Marcello Braglia and Marrazzini, 2020). The food processing industry is characterized by high water and energy demand, contributing to significant waste generation and greenhouse gas emissions (Asgharnejad et al., 2021; Clairand et al., 2020; Garnett, 2013; Nikmaram and Rosentrater, 2019). According to the United Nations, globally about 12% of water resources are used for industrial use, with 56% of it being

consumed by the food and beverage industry, and the global energy consumption of the food sector is about 200 EJ per year, with processing and distribution activities contributing to about 45% of this total (Eslami et al., 2023). In response to these challenges, current research explores innovative solutions such as the adoption of advanced technologies and digitalization (Clairand et al., 2020). Particularly, Digital Twin technology has emerged as a potential solution within the context of Industry 4.0 (Koulouris et al., 2021; Henrichs et al., 2022).

The concept of the Digital Twin (DT), or Digital Twins (DTs), was introduced by Grieves around 2002 in the context of Product Lifecycle Management (PLM). It was later adopted by NASA to describe the development of advanced, high-fidelity simulations for flight certification and testing (Udugama et al., 2021). In 2017, the advisory firm Gartner identified DT as one of the top 10 strategic technology trends, forecasting its widespread adoption among major industrial players (Melesse et al., 2020; Perno et al., 2022). Although DT has been defined in different ways by companies and researchers (Yu et al., 2022), a common definition is still lacking. Conceptually, DT is a living model that looks like, acts like and links-to a physical object or system that can continually be updated with incoming data from the operating environment to monitor the status and forecast future behaviors to improve or optimize decision-making for any time horizon (Melesse et al., 2020, 2021; Yu et al., 2022). DT can look like either a 1-D, 2-D, or 3-D representation of a physical object or a system. These models can either act like a single state (e.g., an average process system state), or discrete event – multiple steady states (e.g., multiple equilibrium process system states), or dynamic state (e.g., model predictive control), which directly or indirectly connect to a physical object or system. The connectivity of the DT (or level of integration) can be categorized based on the flow of data between the digital and physical layers (Bottani et al., 2020; Liu et al., 2021; Botín-Sanabria et al., 2022). For instance, when the digital layer is fully disconnected from the physical layer and no automated data exchange

occurs, it is referred to as a digital model (DM). When the digital layer is partially connected, i.e., it only acquires data from sensors in the physical layer, it is termed a digital shadow (DS). Lastly, when there is full connectivity between the digital and physical layers, with data flowing bidirectionally via sensors, it is referred to as a DT (Liu et al., 2021). The unification of three features namely looks like, acts like and link-to, describes a paradigm shift in DT modeling, distinguishing DT from conventional representations that may capture only the appearance or behavior of a physical object or system without a strong linkage to the physical entity. While all three features are essential for optimal performance, the fidelity of each feature varies depending on the specific purpose and application of the DT (Yu et al., 2022).

DT can be classified based on application level, technique, and functionality (Figure 1). As far as application level is concerned, they may replicate individual units (resource-centric) (e.g., unit operation, equipment, product), the entire system (process-centric) (e.g., production line, packaging line), or a more complex system (hybrid-centric) (e.g., the shop-floor management system) (Park et al., 2020; Henrichs et al., 2022). Regarding techniques, DT models can be categorized as statistical (for process control, design, and product personalization), artificial intelligence (AI), or data-driven, (for monitoring, detection, calibration, verification, and validation), and physics-based (for Multiphysics modelling and simulation). The latter may incorporate mechanistic kinetics of biological and chemical processes. While mechanistic DTs are often capable of simulating the behavior of the real object realistically and comprehensively, the model parameters used in mechanistic DTs can be also quantified, verified, and validated with intelligent DTs using statistical methods and AI methods such as machine learning (ML). The technique is chosen considering the user's needs and application complexity. In terms of DT functionality, each type of DT serves a specific purpose, including real-time monitoring, resource consumption analysis, system failure detection and prediction, process or product optimization, behavior analysis, technology integration, virtual



testing, evaluation and validation, and virtual maintenance. These specific purposes, (Park et al., 2020), are grouped into four main technical functionalities.

- 1 *Prognostic*: DTs can be implemented to predict or forecast future states or behaviors of a process or system. It involves analyzing historical data, current conditions, and various factors to make informed predictions about future outcomes, forecasting the performance of unit operations, predicting insufficiency, and anticipating failures or issues before their occurrence.
- 2 *Reactive simulation*: DTs can enable responding to changes or events in real-time autonomously. Monitoring and dynamic reactions to deviations from expected behavior or predefined thresholds as well as controlling and adjusting the processing variables are the expected outcomes. Thus, it can recommend corrective and preventive actions using monitoring and prediction results.
- 3 *Virtual Commissioning*: For virtual commissioning through DTs testing and validation of new technologies or equipment can be performed in a simulated environment before its real implementation in the processing plants.
- 4 *Synchronization-based Simulation Representation*: utilization of DTs in the representation of synchronization-based simulation involves synchronizing the DT with a physical system to create a simulation model closely mirroring the real process. DT and the physical system are kept synchronized in real-time or near-real-time, allowing the accurate simulation and analysis of the process performance under various conditions. This application is valuable for testing scenarios, optimizing operations, and improving decision-making in complex systems such as transportation networks, energy grids, and smart cities.

Cyber-physical systems (CPS) play an important role in DT technology. In particular, CPS provides the foundation for the DT. It adds advanced capabilities to physical systems through computation and communication, interacting intensively with physical processes, which allows the accurate creation of virtual models or DTs. These DTs, in turn, leverage the capabilities of CPS to monitor, analyze, and control physical systems, leading to precise and efficient management and operation (Wang et al., 2015; Liu et al., 2017; Tao et al., 2019).

In digitally transformed food process operations, DT serves as a virtual replica of assets (i.e., equipment, unit operations), continuously synchronized with real systems via sensors (e.g., temperature and pH sensors) and advanced big data analytic tools (e.g., cloud computing and ML). This innovative approach enables real-time simulation and visualization of the food process operations, enhancing communication, collaboration, and decision-making. Different from conventional computer simulations, which rely on predefined models and scenarios and implement results after the simulation study, DT operates as a dynamic entity, continuously updating and implementing results through operational devices or personnel into real systems. This allows real-time adjustments and immediate actions in real scenarios for optimized processes and improved product quality. Furthermore, DT aims to extend computer simulations beyond their traditional scope of process or product design through virtual prototyping and optimization, offering comprehensive insights into

processes and product development (Maheshwari et al., 2023; Verboven et al., 2020). This technology represents an effort to make simulation and data science tools available not only in the design phase (e.g., through what-if simulations) but also during real-time operations.

Existing studies on food-related DTs have discussed the concept of this technology, exploring various aspects, including its development, applications, utilization, potential benefits and limitations. Notably, these efforts have been predominantly focused on agricultural applications, with comparatively less attention given to other stages of the food system (Henrichs et al., 2022). Particularly, more research efforts on the application of DTs in food processing and manufacturing are needed, given the non-negligible contribution of this sector to the environmental impact. To the best of our knowledge, no prior reviews have comprehensively analyzed and discussed the implementation of DTs within the food processing industry from various aspects with a particular focus on sustainability.

To provide valuable insights for academia, industry, and policymakers to shape the future of digital transformation in the food industry, this review systematically analyzes existing studies on the applications of DT in the food industry, discussing its concept, benefits, and challenges to full adoption. Specifically, this work contributes to the existing body of knowledge on DT by identifying state-of-the-art applications and examining their adoption through both real-world use cases and findings from the literature. Further, it explores DT potential from a sustainability perspective, emphasizing its role in optimizing resource utilization for more efficient and sustainable food processing. Furthermore, it proposes a potential approach within the DT framework to serve as a general tool for supporting sustainability initiatives within the food processing industry. Lastly, it discusses the future impact of DT in shaping the evolution of food processing.

2 Methodology

Given the novelty of DT technology, the state-of-the-art application of DTs in the food processing industry is identified, and seminal works, use cases, existing gaps and the potential for future work in the area are discussed.

To ensure rigor and comprehensiveness, relevant works were selected based on the following criteria: (1) Primary Focus: The literature primarily focus is on DT applications in food processing. The initial inclusion and exclusion criteria were defined using keyword-based searches to filter publications based on their titles and abstracts. Exclusions included duplicates and studies not directly related to DT in the food industry; (2) Types of Literature: Sources included journal articles, conference papers, white papers, book chapters, and press releases. While these sources vary in depth and scientific rigor, they were included to provide a comprehensive overview of DT applications in food processing and capture broader research trends in the field; (3) Literature language: Only publications available in English were considered. (4) Implicit DT Applications: Studies discussing DT enabling technologies without explicitly using the term “Digital Twin” were also considered for inclusion, ensuring that relevant advancements were not overlooked; (5) Final inclusion and exclusion: To further refine the initial selections for the final set, papers that only mentioned DT in food processing in passing were

excluded. Recent review papers' references were examined to include studies that may not have been captured through the initial criteria. This step ensured more exhaustive coverage of literature.

All selected publications were categorized based on a predefined taxonomy (e.g., source type, food sector category, industrial case study and academic case study). Then, they underwent a detailed review, with identified applications systematically analyzed and discussed.

3 Results

A total of 43 case studies were identified from various sources. Figure 2 presents the distribution of these case study sources analyzed in this study. Most studies were published as journal articles (63%), followed by press releases (16%), which include web pages and company websites.

To better capture the current applications of DT in the food processing industry, case studies have been sorted according to the European Union's classification of food processing. The food processing industry is classified into eight distinct categories: (1) meat products, (2) fish products, (3) fruit and vegetables, (4) edible oils, (5) dairy products, (6) grain mill products, (7) bakery, and (8) miscellaneous (e.g., sugar, tea, coffee, condiments, seasonings, snacks, and prepared and canned meals) (Asgharnejad et al., 2021). Within these categories, three main groups are identified: food preservation plants, food ingredient manufacturing plants, and food product manufacturing plants (Maroulis and Saravacos, 2008). Food Preservation facilities primarily utilize agricultural raw materials, often seasonal, employing preservation techniques such as thermal treatment, refrigeration, freezing, concentration, and dehydration. Food Ingredient Manufacturing facilities utilize bulk agricultural products or by-products of food processing to produce various ingredients (i.e., Sugars, starch, flour, oils, proteins, pectin, and gums). These facilities typically utilize operations and equipment units similar to traditional chemical processes. Food Product Manufacturing facilities often employ material transformation and preservation

processes, in addition to packaging, to produce a diverse range of final products for consumers. Figure 3 depicts the application of DT technology across various food processing categories within the three main groups.

DT applications in the food processing within the miscellaneous category, encompassing products like, beverages (such as soft drinks beer, energy drink, fruit juices and water), food products (such as chocolate, French crêpe, honey, ice cream, starch-based foods, condiments), and food ingredients (such as sugar and syrup) (Siemens, 2018; Karadeniz et al., 2019; Bottani et al., 2020; Vignali and Bottani, 2020; Watson et al., 2021; Eppinger et al., 2021; Hong et al., 2021; Koulouris et al., 2021; McLean and Redmond, 2021; Vetter and Strube, 2022; Tshabalala and Kuriakose, 2023; Cabeza-Gil et al., 2023; Tancredi G. P. C. et al., 2023; Coca-Cola, 2023; Force Technology, 2024a, 2024b; George, 2021; Nestlé, n.d.; NVIDIA, n.d.; Siemens, n.d.) represent the most studied category of food processing, accounting for 58% of all categories examined. Within this category, approximately 84 and 16% of the case studies are concerned with food product manufacturing and food ingredient manufacturing groups, respectively, with the food preservation group being overlooked. The DT of fruit and vegetable products represents the second most studied category, constituting 16% of all categories examined. Within this category, both food preservation and food product manufacturing groups received almost equal attention, while food ingredient manufacturing was disregarded. DT applications in the grain, dairy, and meat product categories were studied at similar rates, representing 7, 9, and 7% of the total studies, respectively. Within these sectors, most of the case studies focused on food product manufacturing group, followed by food ingredient manufacturing, and food preservation groups. Finally, the bakery products category was the least explored, while no applications were found in the fish and edible oils categories.

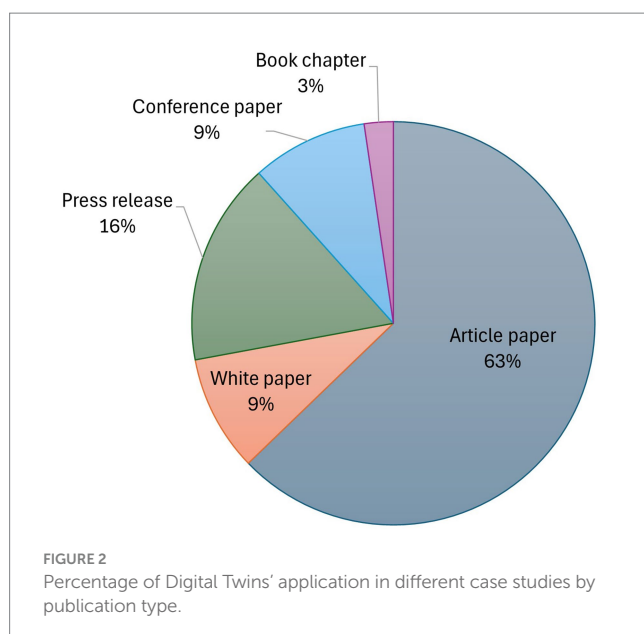
The analysis further differentiated between practical DT applications (industrial case study) and research (academic case study) within the studies, providing insights into the current state of DT adoption at the industrial level (Figure 4). Notably, a clear disparity exists, with a significantly higher number of studies focusing on research compared to industrial use cases.

4 Discussion

4.1 Digital Twin in the food processing industry

4.1.1 Applications

The utilization of DT in the food processing industry has undoubtedly important advantages. It has been adopted across food sectors to optimize operations, enhance product quality, and improve consumers acceptability through the design of personalized products. However, the analyzed case studies revealed a clear lack of applications in the fish and edible oils sectors. This might be due to several factors, as discussed in the following. Indeed, DT technology has been adopted in food sectors where the high complexity of the processes makes streamlining useful to analyze the most critical phases affecting process performance and product quality. Moreover, regardless of whether production is carried out in batch or continuous processes, the utilization of DT technology is attractive for industries



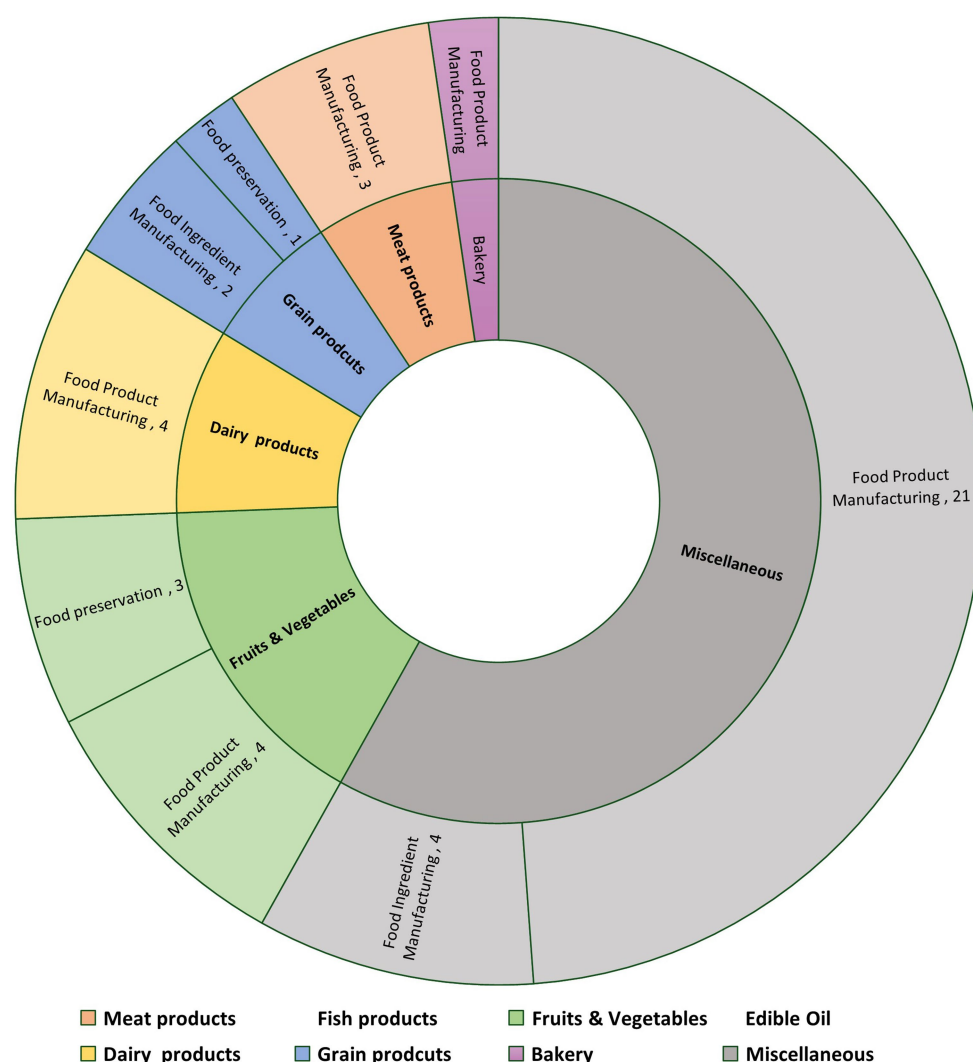


FIGURE 3
Digital Twin applications across food sectors.

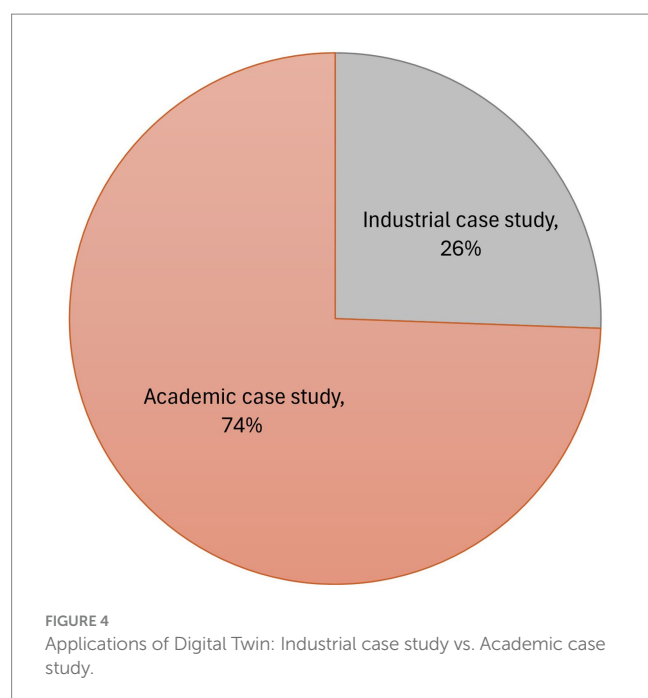
characterized by individualization-based manufacturing (e.g., personalized food products), multi-product manufacturing (e.g., condiments and breweries), and manufacturing of products for which slight changes in processing parameters highly affect the quality (e.g., sugar and dairy production). These industries often prioritize rapid recipe adjustments, efficient management of the productions based on multi-products, effective handling of production uncertainties, and precise control of the processing parameters.

It is worth noting that some implementations already exist in the food industry such as soft drinks manufacturing. The companies use DTs to manage the plant shopfloor and warehouses, as well as streamline processes (Coca-Cola, 2023; NVIDIA, n.d.). Further, other multi-product food companies leverage this technology to optimize operations, enable product personalization, and maintain high-quality standards (Nestlé, n.d.; Siemens, n.d.). The dairy industry uses this technology to maintain product quality, enhance resource efficiency and improve waste management (Force Technology, 2024b). The bakery product producers employ DT to facilitate the management and optimization of existing recipes, and the design of new products

(Force Technology, 2024a). Similarly, the breweries employ the DTs for precise process control, ensuring consistent product quality (George, 2021). However, within the research domain, the number of case studies on the practical implementation of DT is lower compared to those focused on scientific studies. This could be attributed to the company's concerns to publicly disclose the utilization of DT technology and its advancement to maintaining a competitive advantage. Additionally, the implementation of DT often involves the collection and analysis of sensitive data, which companies may be reluctant to share for confidentiality reasons. Furthermore, many DT applications are still in their early stages, and companies may prefer to achieve more robust results before their dissemination.

4.1.2 Purpose of use

The adoption of DT technology is driven by production and market factors, such as the need to meet increased demand or adapt to evolving market preferences, align with specific nutritional standards, and packaging sizes (Koulouris et al., 2021). Additionally, the increased competition in the business environment compels



companies to look beyond cost reduction, and consider as key factors the improvement of product quality, productivity, and process efficiency (Perno et al., 2022). Further, food companies have to cope with low-profit margins while being challenged to face market changes by reducing time-to-market while developing new and flexible processes for a wide range of products (Koulouris et al., 2021). The employee-related factors play a role, with companies leveraging DTs to enhance creativity and cooperation between employees and offer virtual reality-based training programs and increase workplace safety by identifying potential hazards (Henrichs et al., 2022).

DT is deemed implemented when it incorporates as key elements the physical object or process that should be twinned, a virtual model representing the essential properties of the physical counterpart, and the connection between the two (Kritzinger et al., 2018; Xia et al., 2020; Ricci et al., 2021). It is worth mentioning that if there is lacking of or insufficient data available between the digital layer and its physical counterpart, it is not possible, by definition, to consider the model of the system as a DT. In the food processing industry, DTs have been implemented at different stages, using various enabling technologies for system architectures, each encompassing a specific purpose for their use. These stages are the design, processing, and service, and, in turn, are subdivided into sub-categories considering their specific purposes as follows.

4.1.2.1 Design stage

- 1 *Optimization*: DT utilization can assist in individuating the optimal design parameters to maximize process efficiency and minimize resource consumption. It can be employed to design new products, new processes and retrofitting the existing ones to enhance product quality, productivity, and efficient use of resources.
- 2 *Data Generation*: In situations where sufficient data for process design are lacking, for instance when only lab-scale data are available, DT can be employed to generate the necessary data.

This can help in rebalancing datasets or estimating operating conditions or product characteristics, facilitating the setup of accurate models, through techniques such as ML, to be fed into optimization models.

- 3 *Virtual Evaluation, Verification, and Validation*: DTs serve as cost-effective tools for evaluating, verifying, and validating designed processes and products in a virtual environment.

4.1.2.2 Processing stage

- 1 *Process monitoring*: DTs could offer real-time monitoring by integrating essential data with visual models. It can combine historical, real-time, and predictive data to track past performances, monitor current operations, and forecast future outcomes. Thus, not only current data can be presented but DT could help in understanding situations and optimizing decisions.
- 2 *Process control*: Conventional methods for process control are based on physical measurements, and models should be used for predictive control. DTs, instead, enhance process control by leveraging the connection between virtual and physical components to eliminate disturbances and maintain quality specifications.
- 3 *Process prediction*: Variations in processing variables, such as raw material characteristics fluctuations, pose challenges. DTs predict how these variations impact processing conditions, leveraging soft sensing technologies like ML to forecast the trend of critical variables that are difficult or costly to be measured directly.
- 4 *Process optimization and production planning*: Conventional process optimization and production planning methods are affected by disturbances and uncertainties since they rely on static information. DTs vastly improve the effectiveness of optimization and planning processes by providing both monitored and predicted data.

4.1.2.3 Service stage

- 1 *Fault Detection and Diagnosis*: Fault locations can be pinpointed by comparing process variables from both virtual and physical processes. DTs facilitate fault diagnosis, enabling the identification of fault types and/or affected resources.
- 2 *Virtual Testing*: As a digital replica of the physical object, DTs allow testing operations in scenarios where failures could result in significant losses or damages. Unlike traditional simulation, DTs offer a highly realistic and accurate simulation environment. The identical virtual settings enable thorough exploration and testing without the inherent risks associated with physical systems.
- 3 *Predictive maintenance*: Like process prediction, predictive maintenance can be managed by DTs that can provide information on disturbances and uncertainties, thus providing more accurate maintenance times, such as cleaning-in-place scheduling.

Table 1 shows the results reported in the literature on the implementation of DTs in food processing, including the phases and specific purposes of their implementation and the main findings. For

TABLE 1 Overview of key findings on the implementation of DT in food processing industry.

Phase	Specific purpose	Reference	Findings
Product	Optimization	Hong et al. (2021)	DT technology enabled the design of Microwave-Assisted Thermal Sterilization (MATS) systems, optimizing parameters like phase shifts and cavity dimensions to improve heating uniformity and throughput for ready-to-eat meals.
		Vetter and Strube (2022)	DT model for sugar crystallization was used to evaluate the influence of different factors such as temperature, agglomeration, or crystal attrition on sugar quality.
		Force Technology (2024a)	DT technology facilitated the management and optimization of existing bakery products, the design of new ones, and the presentation of both current and potential new products to customers, even prior to real production.
	Data generation	Nikitina and Chernukha (2020)	DT enabled meat product personalization by helping developing recipes for new food products with a complex composition and characteristics. Further, testing meat via DT allowed saved time, and resources in experimentation.
	Virtual testing	Siemens (2018)	DT enabled inline packaging design with considerable time savings for new PET bottle development.
		Siemens (2018)	DT enabled virtual testing, leading to greater efficiency and a significant reduction of cycle times in new energy drink development.
Process	Monitoring	Siemens (2018)	Fully automated plant and real-time monitoring were achieved by DT of a cheese plant, eliminating many actions previously performed by workers interventions.
		Dolci (2017)	DT of malthouse allowed real-time monitoring and predicting of how process parameters, such as CO ₂ concentration, temperature, humidity and pH, vary in the three steps of the malting process.
		George (2021)	DT facilitated real-time monitoring of the fermentation process, ensuring consistent product quality. Alongside that, it provided operators with critical insights for maintaining equipment uptime, enhancing production efficiency, and minimizing bottlenecks.
		Nestlé (n.d.) and Siemens (n.d.)	DT enabled a comprehensive monitoring system, leveraging advanced DT-enabling tools to oversee facility assets and materials. It facilitated the simulation of the entire production process, from raw materials to finished products. Key achievements included enhanced product design and personalization, process optimization, improved predictive maintenance, and strengthened quality control.
	Control	Ozden and Kılıç (2022)	DT controlled the process of banana drying by using images obtained just from a digital camera. Further, the developed DT could end the drying process by estimating the drying progress without using an extra sensor or equipment.
		Raut et al., (2022)	DT optimized the drying process by effectively controlling process parameters, leading to higher or similar carotenoid retention in carrot slices, shorter drying times, and reduced energy consumption.
		McLean and Redmond (2021)	DT of chocolate plant enabled better control of the chocolate bar production process and an improvement of the consistency and uniformity of the product across the processing lines.
		Tancredi G. P. C. et al. (2023)	DT of filters in a milling plant demonstrated its capability to control the velocity of the polluted air in the manifold, ensuring the optimal solid particle concentration in the air before discharging it in the atmosphere.
		Eppinger et al. (2021)	DT of a ketchup plant improved monitoring of the temperature of the product to optimize energy use efficiency and product quality.
		Tancredi G. et al. (2021)	DT technology enabled precise monitoring of pasteurization process parameters, reducing safety risks during pilot plant testing.
		Eppinger et al. (2021)	DT of a milk powder dryer allowed optimizing the drying process by modifying the airflow rate, direction and flow conditions in the nozzles resulting in improved product quality. Further, the reduction in operating costs was achieved, avoiding the construction of an expensive pilot plant.

(Continued)

TABLE 1 (Continued)

Phase	Specific purpose	Reference	Findings
	Prediction	Tancredi et al. (2022)	DT AI-based pasteurizer for liquid foods was proven effective enough in predicting anomalies.
		Watson et al. (2021)	Coupling sensors and DT allowed predicting the endpoint of fermentation of beer, preventing over or under-fermenting in breweries and the associated resource loss.
		Schemminger et al. (2024)	DT effectively predicted the drying behavior and quality retention of carrot slices by assessing the biological variability among individual slices during the drying process.
		Bottani et al. (2020)	DT of a juice pasteurizer enabled the prediction of potential anomalies in the unit by comparing the results of the simulation model with real-time data from the plant.
		Vignali and Bottani (2020)	DT of a juice pasteurizer enabled the prediction of pressure and temperature during pasteurization based on real data taken from sensors.
		Watson et al. (2021)	Intelligent sensors with ML enabled the real-time monitoring and optimization of the mixing processes of honey-water, accurately predicting the endpoint of the mixing stage.
		Nget et al. (2023)	The DT model enabled the prediction with high accuracy of cooking temperatures and moisture loss in Cambodian pâté, resulting in enhanced food safety and quality in the preparation of Cambodian pâté
		Watson et al. (2021)	Intelligent sensors, as enablers of DT, improved potato tuber quality assessment by predicting dry matter content and classifying potatoes by size, eliminating the need for destructive methods. This led to enhanced resource efficiency and reduced waste in food manufacturing processes.
		Cabeza-Gil et al. (2023)	The DT enabled real-time monitoring of crêpe properties, including temperature, color, and weight loss, with high accuracy. This allowed for precise prediction of cooking completion time based on user-defined criteria.
	Optimization and planning	Maheshwari et al. (2023)	DT of an ice cream plant enhanced the existing machine and work efficiency and effectiveness.
		Koulouris et al. (2021)	DT aided in achieving efficient production in a brewery. Long-term planning can be performed utilizing a digital model able analyzing productivity while considering the effects of process variabilities to individuate the way the production goals can be achieved, rationalize production plans or manage production changes.
		Dąbrowska et al. (2022)	DT enabled scheduling the sequence of a sugar packing machine and preventing the occurrence of problems in a sugar packaging line.
		Tshabalala and Kuriakose (2023)	DT assisted in reducing the cycle between workstations and pre-determine possible bottlenecks that might occur during production.
		Coca-Cola (2023)	For customer-specific mixed orders, DT simulated the bottling plant, facilitating the analysis of order data and warehouse layout to determine optimal picking routes, Yard management efficacy optimization and waste reduction were achieved.
		NVIDIA (n.d.)	DT enabled automation of warehouse operations and workflow, maximizing inventory storage capacity, increasing throughput, and minimizing the space, equipment, and labor required.

(Continued)

TABLE 1 (Continued)

Phase	Specific purpose	Reference	Findings
Service	Fault Detection and Diagnosis	Eppinger et al. (2021)	DT technology corrected the positioning of cheese on the belt conveyor by using camera systems to detect and rectify misalignments.
		Tancredi G. P. C. et al. (2023)	DT-based control system in a pasteurizer for liquid foods showed a fast response and good robustness in controlling the pasteurization process by adjusting automatically the pressure setpoint, preventing any potential system failure.
		Siemens (2018)	DT of a syrup mixing process enabled the prevention of possible bottlenecks and optimize the production process as a result of optimized monitoring, planning and scheduling.
		Gericke et al. (2019)	DT of water bottling enabled the identification of points where faults could occur allowing minimizing maintenance scheduling. Additionally, DT could help detecting drops in production rates and individuating the bottlenecks where these problems might occur providing self-correction actions.
		Solari et al. (2023)	The DT enabled the accurate assessment of the filter's operating state, identification of failure events or operating anomalies, and prediction of the Remaining Useful Life of the cyclone bag filter.
	Predictive maintenance	Simeone et al. (2018) , Simeone et al. (2020) , Watson et al. (2021)	DT coupled with smart monitoring AI improved the management of the CIP process by facilitating the evaluation of fouling occurrence, enabling timely alerts to operators on cleaning efforts adequacy within a specified timeframe.
		Force Technology (2024b)	DTs facilitated well-planned CIP by monitoring biofilm growth in the heat exchanger in real time during production and detecting potential sources of bacterial growth and pathogens.
		Karadeniz et al. (2019)	DT technology for ice cream machines was tested, demonstrating its ability to enhance fault monitoring, performance assessment, and predict potential usage and/or level of depreciation.
	Virtual testing	-	-

the sake of clarity, the specific purpose of each study is reported, regardless of the additional functionalities that might be achieved.

As shown in [Table 1](#), the implementation of DT technology in food processing was mostly concerning the process phase, being control and prediction of the most targeted functionalities. As mentioned before, some studies achieved additional functionalities of DT applications besides the specific purpose for their use. For instance, to mention a few, [Bottani et al. \(2020\)](#) developed a DT for a fruit juice pasteurization unit to predict potential anomalies and enhance worker safety. Simultaneously, DT was used to control process parameter variations. In the study case of carrot slice drying conducted by [Schemminger et al. \(2024\)](#) the specific purpose of DT was the prediction of product quality, while monitoring and controlling were concurrently considered as functionalities of the DT. Thus, it can be highlighted that DT can be exploited for multiple functionalities simultaneously and fulfill the requirements of more controlled and efficient food processing operations.

4.1.3 Tools, methods and technologies for digital Twin system architecture

DT has been supported by various technologies and tools (from simulations to agents, from graphical representations to service platforms), each serving specific purposes aligned with the user's ultimate goal ([Crespi et al., 2023](#)). Modeling and simulation are pivotal components of DT technology, particularly in complex processes. Commercial process simulator software, such as SuperPro Designer,

Aspen Plus, Aspen HYSYS, etc., are widely employed for constructing virtual plants ([Ureta and Salvadori, 2022](#)). Typically, these process simulators utilize first-principles modeling, also known as white-box modeling, which relies on a deep understanding of physical–chemical phenomena underneath the process. Previous studies carried out for the food processing and chemical processing industry ([Koulouris et al., 2021](#); [Barbero-sánchez et al., 2024](#)) have demonstrated the significant role of process simulators within the DT framework. These tools are characterized by standardized methodologies and robust technical support, ensuring the quality and reliability of DT applications in complex processes ([Yu et al., 2022](#)). Computational fluid dynamics (CFD) simulation tools (i.e., COMSOL Multiphysics, Ansys, etc.) also contribute significantly to DT frameworks. While these tools are inherently slow and cannot provide real-time or near-real-time simulation feedback, which is one of the key aspects of DT, they can be integrated with significant powerful tools, such as AI. For instance, ML models can be trained on a set of CFD-generated data to build quickly accessible models for real-time simulation, enabling faster predictions. This approach, explored in a case study for oven automation, was enabling real-time simulations for optimized thermal processing control ([Kannapinn et al., 2022](#)). In addition, CFD simulations can be launched in advance, building a database, which can then be used for real-time system control by comparing expected outcomes with sensor data to detect faults or anomalies, as discussed by [Solari et al. \(2023\)](#). Overall, these approaches allow for the creation of more efficient and responsive DT systems. Intelligent sensors and

cloud platforms are advanced tools that enable the development and implementation of DT. These tools leverage data-driven (black-box) modeling, powered by big data analysis, IoT, and machine learning. While this approach is gaining traction in food processing in the context of Industry 4.0, hybrid modeling, combining white-box and black-box modeling approaches, is increasingly being considered in food-related DT studies. For example, (Tancredi et al., 2022) conducted a hybrid modeling study of a heat exchanger for monitoring and anomalies detection. Fundamental equations were incorporated in the model developed in LabVIEW environment for simulation. Additionally, Python was employed to develop an ML algorithm, enabling full process automation and autonomous fault detection, allowing real-time adjustments to optimize performance. Hybrid modeling approach offers a balanced integration of theoretical foundations and empirical data, providing a more robust and reliable DT function (Eppinger et al., 2021; Tancredi et al., 2022). Table 2 provides an overview of the diverse tools employed for DT construction within the analyzed food processing case studies.

4.1.4 Digital Twin for resource efficiency enhancement and waste management

The application of DT technology in the food sector can be crucial to meeting the societal demand for increased sustainability by improving resource efficiency and reducing water and energy consumption and emissions. Therefore, the driving factors for the use of DTs are not only the needs of the food industry to meet market

demands and maintain competitiveness through the development of new products, quality enhancement, personalized food product design, and productivity improvement, but also a commitment to reduce its environmental footprint. Therefore, the use of DT technology can be seen as a significant advantage for the management of this last problem. For instance, DT facilitates precise control of production lines (Noor Hasnan and Yusoff, 2018; Clairand et al., 2020). This enables real-time monitoring of potential water and energy losses, allowing the implementation of solutions to prevent such losses (Clairand et al., 2020; Ojo et al., 2018). Measuring and analyzing specific variables and parameters of unit operations for water and energy usage through DT enables the identification and anticipation of potential issues. This proactive approach allows for the adjustment of process parameters, leading to improved water and energy efficiency and reduced waste. For example, in the ketchup processing industry (Eppinger et al., 2021), maintaining ketchup temperature above a certain threshold throughout the process is crucial to prevent bacterial proliferation, although at the cost of significant thermal energy consumption. DT technology can optimize thermal management systems, allowing for a reduction in the safety margin for target temperature settings. This not only decreases thermal energy consumption, leading to substantial cost savings but also preserves product quality. Similarly, in the milk powder industry (Eppinger et al., 2021), the drying process plays a pivotal role in determining end-product quality. Given its energy-intensive nature, optimizing the drying process typically requires

TABLE 2 A summary of different tools and technologies used in the case studies for constructing system architecture of DT technology.

DT enablers	Tools	References
Process simulator tools for steady state or dynamic systems	SuperPro designer [®] process simulator, AnyLogic, Aspen modular, Simulink-MATLAB, SIMIT simulator and AmeSim	Gericke et al. (2019), Koulouris et al. (2021), Maheshwari et al. (2023), Siemens (2018), Tshabalala and Kuriakose (2023), and Vetter and Strube (2022)
Computer-aided-design CAD tools	Siemens PLM NX CAD Software and Ansys SpaceClaim	Siemens (2018) and Solari et al. (2023)
Tools for planning, scheduling and management	SchedulePro [®] , Siemens SIMATIC IT R&D Suite, Siemens MoM system and TIA portal and COMOS	Koulouris et al. (2021) and Siemens (2018)
Computational fluid dynamics (CFD) simulation tools*	Ansys Fluent and COMSOL [®] Multiphysics	Force Technology (2024a), Schemminger et al. (2024), and Solari et al. (2023)
Computational Electromagnetics (CEM) simulation tool	QUICKWAVE	Hong et al. (2021)
Programming language	Python and G-Code	Cabeza-Gil et al. (2023), Tancredi et al. (2022)
Graphical programming environment tools	LabVIEW	Bottani et al. (2020), Tancredi G. et al. (2021), Tancredi G. P. C. et al. (2023), Tancredi et al. (2022), and Vignali and Bottani (2020)
Intelligent platforms	Microsoft Azure tool	George (2021), McLean and Redmond (2021), Microsoft (n.d.)
Technologies	AI-powered sensors, monitoring systems, cameras, IoT, Augmented Reality (AR) and Virtual Reality (VR)	Coca-Cola (2023), Dolci (2017), Eppinger et al. (2021), Force Technology (2024b, 2024a), Karadeniz et al. (2019), Nestlé (n.d.), Nikitina and Chernukha (2020); NVIDIA (n.d.), Ozden and Kılıç (2022), Raut et al. (2022), Siemens (n.d., 2018), Simeone et al. (2018, 2020), Valero et al. (2023) and Watson et al. (2021)

*Some tools, such as CFD simulation software, do not support data acquisition, automation, or real-time integration. However, they can function as a DT when integrated with powerful technologies like AI. It is worth noting that some tools integrate the Monte Carlo simulation technique to support statistical and computational analyses to enhance DT functionality.

empirical testing. By leveraging DT technology to adjust airflow directions and processing conditions, energy efficiency can be improved alongside product quality, while reducing the number of experimental trials. In the flour industry, precise control of the air velocity in pneumatic conveying systems is vital for both environmental safety and product quality (Tancredi G. P. C. et al., 2023). Optimizing this parameter can significantly improve the system's energy efficiency. In honey-based product manufacturing (Watson et al., 2021), inefficient mixing can result in off-specification products and excessive energy consumption. The mixing process can leverage DT to predict the remaining time for complete mixing, enabling better scheduling of batch processes and enhancing productivity. Thus, preventing under-mixing and over-mixing, product rework or disposal is minimized, while excess energy usage is reduced. DT technology also contributes to water efficiency in Cleaning-In-Place (CIP) systems in the food industry (Simeone et al., 2018; Simeone et al., 2020). The food industry can leverage this technology for real-time monitoring and optimized planning of CIP processes. For example, in processes involving tanks of product concentrate, DT can evaluate fouling levels during cleaning, providing timely alerts to operators regarding cleaning adequacy within specified timeframes, thereby preventing both over cleaning and insufficient cleaning (Simeone et al., 2020). Furthermore, in the dairy industry, DTs can facilitate well-planned CIP by monitoring biofilm growth in the heat exchanger in real time during production and detecting potential sources of bacterial growth and pathogens. This approach ensures proper hygiene, maintained quality, and reduced downtime, while simultaneously improving water and energy efficiency (Force Technology, 2024b). Beyond water and energy use efficiency, DT can mitigate food waste during production. For example, DTs can be utilized for predictive maintenance of assets like pasteurizers, contributing to more efficient and less wasteful food production (Force Technology, 2024b). Furthermore, considering the variability of raw materials due to seasonal factors, DT technology offers an adaptive approach to adjusting processing parameters, such as machine settings, based on raw material quality or properties, thereby minimizing waste. Overall, DT could contribute to the growth of sustainable processes by optimizing the use of raw materials, water and energy, enabling food waste to be reduced (Eppinger et al., 2021; Watson et al., 2021).

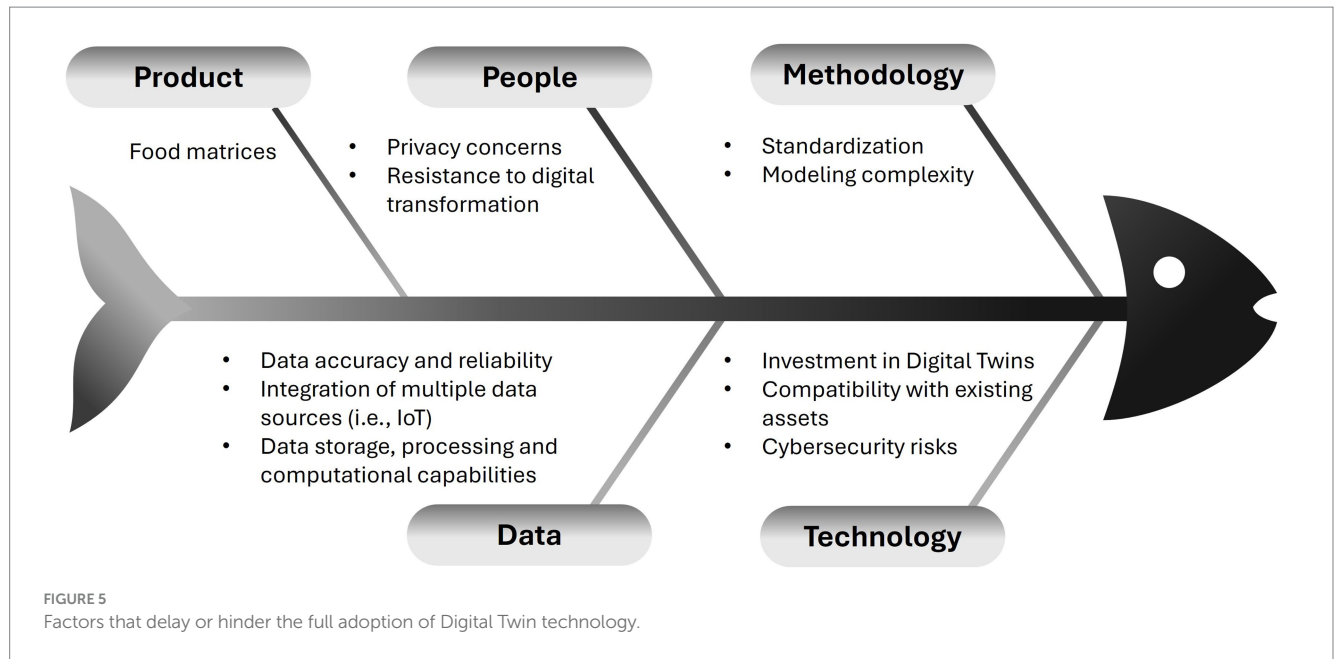
4.2 Digital Twin as a general tool for supporting sustainability initiatives

In food processing, most design and optimization problems are aimed at several objectives, which can often be contradictory (Abakarov et al., 2013; Madoumier et al., 2019). Potential antagonistic effects can arise when optimizing multiple objectives, as maximizing one may lead to the minimization of one or several others (Rangaiah, 2009; Rangaiah et al., 2020). For instance, maximizing food product quality (texture, nutrient concentration, flavor, etc.) often conflicts with process performance objectives, such as minimizing utility consumption, maximizing profit, or ensuring safety (Madoumier et al., 2019). Optimal solutions can be achieved through a multi-objective optimization (MOO) approach (Rangaiah, 2009; Rangaiah et al., 2020). MOO offers well-balanced solutions for the single-unit operation and the entire process, simultaneously investigating and

estimating potential savings (Cerdeira-Flores et al., 2022). This approach can be integrated into the DT framework to serve as a versatile tool for implementing and assessing the effectiveness of sustainability initiatives in food processing. Recent studies in other disciplines have demonstrated the effectiveness of this approach in identifying optimal trade-offs between conflicting objectives within DT framework. For instance, Wang et al. (2023) investigated the scheduling optimization of laminar cooling water supply systems for hot rolling mills to enhance energy efficiency in the steel industry. The optimization model was designed to minimize multiple objectives simultaneously, primarily focusing on reducing the electrical energy usage in the pumping system while ensuring adequate water supply and operational efficiency. This optimization model was introduced in a DT framework, enabling a new mechanism for scheduling that includes virtual-real response, interaction, control, and iterative optimization. The proposed scheduling system significantly reduced energy consumption while ensuring the cooling requirements. This demonstrated the effectiveness of the DT model in optimizing resource use in industrial applications. Guo et al. (2024) proposed a novel DT model for geothermal heating systems to be utilized in buildings to address supply-demand mismatches. The authors integrated MOO within the DT framework to enable simultaneous optimization of the costs, geothermal energy utilization, and carbon emissions. This approach facilitated accurate heating demand prediction and optimal control of storage systems and heat pumps, maximizing geothermal energy use while minimizing both the costs and the emissions. The authors emphasized that this approach is an effective mean of enhancing energy sustainability. Therefore, in the perspective of a wider utilization of DT technology in the food processing industry, the integration of MOO into DT is highly valuable to enhance the usefulness and maximize the functionality of this model and enable more effective product and process design and optimization.

4.3 Challenges and limitations

While significant progress has been made in developing DT models for the food industry, large-scale deployment remains challenging. This is due, in part, to the need for advanced mathematical, numerical, and computational methodologies to ensure robustness and scalability (Bianco et al., 2022; Kannapinn et al., 2022). Beyond DT model development, recent research has highlighted general implementation challenges (Fuller et al., 2020; Henrichs et al., 2022; Melesse et al., 2020, 2021; Perno et al., 2022; Verboven et al., 2020; Wagner et al., 2019). For instance, Fuller et al. (2020), noted similarities between DT implementation challenges and those encountered in data analytics and the IoT, including data security, data acquisition, communication, storing, sorting, and analysis. Incorporating functional requirements into the DT including the monitoring of asset operations, the measurement of key performance indicators (KPIs), the materials data, the notification of unacceptable fluctuations and the use of simulation to identify potential adjustment actions, necessitates a vast amount of data, potentially hindering DT's operational efficiency. Specifically, deep learning algorithms are considered highly energy-intensive tools, exacerbated by the increasing volumes of IoT data transmitted over networks (Yu et al., 2022).



Further, a significant increase in computational requirements could lead to a trade-off between marginal benefits and the power consumed, which may counteract the intended purpose. Other studies have identified further implementation challenges, including the lack of a standardized methodology for information transfer between physical and virtual objects (Melesse et al., 2020, 2021; Perno et al., 2022), the need for a consistent framework (Henrichs et al., 2022; Wagner et al., 2019), and the complexity of model implementation given the intricate nature of food matrices (Verboven et al., 2020). Furthermore, the reluctance of some food companies to adopt emerging technologies, coupled with concerns over high investment costs and data security, also hinders widespread DT implementation within the food sector (Melesse et al., 2020, 2021; Verboven et al., 2020; Henrichs et al., 2022; Krupitzer et al., 2022; Perno et al., 2022). In Figure 5, the Ishikawa diagram is reported to highlight the factors that delay or hinder the full adoption of DT technology.

4.4 Related studies and future direction

Recent publications have investigated the prerequisites for developing and implementing DTs in the process industry, highlighting their potential benefits, challenges, and essential enabling technologies (Lee et al., 2013; Eisen et al., 2020; Verboven et al., 2020; Xia et al., 2020; Liu et al., 2021; Perno et al., 2022). DT concepts and capabilities are still evolving, and existing literature reviews offer valuable insights in this context, however, efficient resource management throughout the entire process operations have not been highly prioritized. For instance, Verboven et al. (2020) underlined that a comprehensive, multidisciplinary approach is required for a successful deployment and operation, highlighting the benefits of DTs in food processing operations. Nikitina and Chernukha (2020), whose work was focused on the utilization of DTs in food product development, underscored the

efficiency and cost-saving benefits of DTs for testing new food product recipes virtually. Pylianidis et al. (2021) considered DT applications in food systems, focusing only on agriculture production, while Henrichs et al. (2022) reviewed DT applications in a broader context in the food industry, primarily focusing on the food supply chain. The latter highlighted the challenges and potentials of implementing this technology in the food industry with a focus on the supply chain. Kucha and Olaniyi (2024) studied the potential implementation of DTs in the meat industry utilizing the latest digital tools like IoT sensors for product quality improvement, highlighting the significance of this technology in the meat industry.

Differently from previous review papers, in this work, the applications of DTs in food industry have been thoroughly analyzed, with a specific focus on their potential and challenges to sustainability outcomes. The paper specifically targeted the food processing industry, providing a classification of the applications of DTs emphasizing the key elements, the model bases, functionalities and the purposes of their use (Table 3). It also sheds light on the technologies, commercial software and methods utilized for constructing the system architecture of DTs, offering insights into target units, products, and processes. The potential contribution of DTs in providing suggestions to increase the sustainability of the food processing industry, with particular attention on water and energy management, was analyzed and discussed. However, the limited number of publicly available industrial case studies did not allow fully capture the scope of DT adoption across the sector. Efforts are needed to get information on its implementation extent in the food industry as well as the factors that hinder its wider adoption.

Overall, being DT an emerging technology, standards and frameworks must be established and DT modeling methodology must be improved, enabling applications to enhance resource use efficiency and minimize waste generation in food processing operations.

TABLE 3 Summary on the Digital Twin technology: applications and development approach.

Application	Twinned system	Model feature	Model basis	Connectivity	Application level	Functionality	Reference
Baked product	Oven	3-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Reactive simulation Synchronization-based Simulation	Force Technology (2024a)
Banana	Drying system	3-D Dynamic	Statistical-Based Data-Driven	DT	Resource-centric	Virtual Commissioning	Ozden and Kılıç (2022)
Beverage/ soft drinks	Tube-in-tube heat exchanger	2-D Dynamic	Physics-Based Data-Driven	DT	Resource-centric	Prognostic Reactive simulation	Tancredi et al. (2022)
	Bottling plant	3-D Dynamic	Statistical-Based Data-Driven	DT	Process-centric	Prognostic Synchronization-based Simulation	Coca-Cola (2023)
	Warehouse	- Dynamic	Statistical-Based Data-Driven	DT	Process-centric	Prognostic Synchronization-based Simulation	NVIDIA (n.d.)
Brewery	Plant units	2-D Discrete Event	Physics-Based Statistical-Based	DT	Process-centric	Prognostic Reactive simulation Virtual Commissioning	Koulouris et al. (2021)
	Fermenter	- Dynamic	Data-Driven	DT*	Resource-centric	Prognostic	Watson et al. (2021)
	Plant units	- Dynamic	Physics-Based Statistical-Based Data-driven	DT	Process-centric	Prognostic Synchronization-based Simulation	George (2021)
Carrot	Drying system and the product	3-D Dynamic	Physics-Based	DS	Resource-centric	Prognostic Virtual Commissioning	Schemminger et al. (2024)
	Drying system	2-D Dynamic	Physics-Based	DT	Resource-centric	Virtual Commissioning	Raut et al. (2022)
Cheese	Belt conveyor	2-D Dynamic	Statistical-Based Data-Driven	DT	Resource-centric	Prognostic Reactive simulation Synchronization-based Simulation	Eppinger et al. (2021)
	Plant units	3-D Dynamic	Statistical-Based Data-Driven	DT	Process-centric	Prognostic Reactive simulation	Siemens (2018)
Chocolate	Plant units	- Dynamic	Statistical-Based Data-Driven	DT	Process-centric	Prognostic Reactive simulation	McLean and Redmond (2021)
Condiments and other products concentrate	Process tank	2-D Dynamic	Statistical-Based Data-Driven	DS*	Resource-centric	Prognostic	Simeone et al. (2018) , Simeone et al. (2020) and Watson et al. (2021)
Dairy products	Plate heat exchanger	- Dynamic	Physics-Based Data-Driven	DT	Resource-centric	Prognostic	Force Technology (2024b)
Drink bottles	Bottling machine	3-D Dynamic	Physics-Based	DT	Resource-centric	Virtual Commissioning	Siemens (2018)
Energy drink	Product	3-D Dynamic	Physics-Based Statistical-Based	DT	Resource-centric	Virtual Commissioning	Siemens (2018)
Flour	Filtration system	2-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Tancredi G. P. C. et al. (2023)
Fruit juice	Pulsed electric field (PEF) system	2-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Reactive simulation	Bottani et al. (2020)
	Pasteurization system	2-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Reactive simulation	Vignali and Bottani (2020)

(Continued)

TABLE 3 (Continued)

Application	Twinned system	Model feature	Model basis	Connectivity	Application level	Functionality	Reference
French crêpe	French crêpe	3-D Dynamic	Physics-Based Data-Driven	DT	Resource-centric	Prognostic	Cabeza-Gil et al. (2023)
Honey	Mixer	- Dynamic	Statistical-Based Data-Driven	DT*	Resource-centric	Prognostic	Watson et al. (2021)
Ice cream	Plant and management	2-D Dynamic	Physics-Based	DT	Hybrid- Centric	Prognostic Synchronization-based Simulation	Maheshwari et al. (2023)
	Ice cream machine	3-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Synchronization-based Simulation	Karadeniz et al. (2019)
Ketchup	Plant units	3-D Dynamic	Statistical-Based Data-Driven	DT	Process-centric	Prognostic Synchronization-based Simulation	Eppinger et al. (2021)
Liquid food (fruit juice, milk, beer)	Pasteurization system	2-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Reactive simulation	Tancredi G. et al. (2021) and Tancredi G. P.C. et al. (2023)
Malt	Malthouse	- Dynamic	Physics-Based	DT	Process-centric	Prognostic Synchronization-based Simulation	Dolci (2017)
Meat (pork meat and cattle meat)	Food system	- Dynamic	Statistical-Based Data-Driven	DT	Hybrid- Centric	Prognostic Reactive simulation Virtual Commissioning	Valero et al. (2023)
	Product	- Single State	Physics-Based	DM	Resource-centric	Virtual Commissioning	Nikitina and Chernukha (2020)
	Product	3-D Dynamic	Physics-Based Statistical-Based	DT	Resource-centric	Virtual Commissioning	Nget et al. (2023)
Milk powder	Spray dryer	-	Physics-Based	DT	Resource-centric	Virtual Commissioning	Eppinger et al. (2021)
Multi-products	Product and Plant level	- Dynamic	Statistical-Based Data-Driven	DT	Resource and Process-centric	Prognostic Reactive simulation Virtual Commissioning Synchronization-based Simulation	Nestlé (n.d.) and Siemens (n.d.)
Potato	Product	-	Statistical-Based Data-Driven	DT*	Resource-centric	Prognostic	Watson et al. (2021)
Starch-based food	Thermal sterilization system	3-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Hong et al. (2021)
Sugar	Crystallizer	2-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Vetter and Strube (2022)
	Packing machine	2-D Dynamic	Physics-Based Statistical-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Dąbrowska et al. (2022)
Syrup	Mixer	3-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Reactive simulation	Siemens (2018)
Water bottling	Bottling line	3-D Dynamic	Statistical-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Gericke et al. (2019)
	Water plant	2-D -	Statistical-Based	DS	Process-centric	Prognostic Virtual Commissioning	Tshabalala and Kuriakose (2023)
Wheat	Cyclone Bag Filter	3-D Dynamic	Physics-Based	DT	Resource-centric	Prognostic Virtual Commissioning	Solari et al. (2023)

1-D, 2-D and 3-D are the dimensional representation of the digital object; DM, DS, DT are the digital model, digital shadow and Digital Twin. *DT and DS were not explicitly mentioned, but their enabling tools were utilized to achieve the objectives of the studied scenario.

DT can either replace current systems or be integrated into existing tools and methods to enhance their functionality beyond traditional limits, offering a powerful solution for managing complexity more effectively. From our perspectives, since DT can be applied at any system level and time horizon, it is particularly valuable in scenarios where human intervention requires significant intellectual and resource efforts.

5 Conclusion

To conclude, Digital Twin (DT) technology holds a significant promise for revolutionizing the food processing industry. Its potential spans a range of holistic solutions, including real-time control, production scheduling, technology upgrades, asset diagnosis, maintenance, and optimization for more efficient and sustainable processes. However, open questions need to be addressed to ensure broad adoption across all food processing categories. Current DT case studies in the food processing industry remain limited, with a primary focus on investigating and demonstrating the feasibility of applications and use-cases. This review analyzed its applications across various food processing categories, distinguishing between its practical adoption and existing scientific literature. Key aspects, including functionalities, purpose of use, and challenges to full adoption, were discussed to provide insights into its status. The potential approach within the DT framework to serve as a general tool for supporting sustainability initiatives within the food processing industry was examined. Furthermore, the review emphasized the need for further research to bridge existing gaps. Standardization efforts, the development of a consistent framework, and advancements in modeling and simulation techniques are required to allow the growth and adoption of the DT within food sectors to achieve true digitalization within this complex industry. Addressing these challenges will be pivotal in unlocking the full potential of DT technology, paving the way for smarter, more sustainable food processing operations.

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