

Integration of Digital Twin Modeling and Intelligent Scheduling Frameworks in the Food Processing Industry - A Review

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Abstract

The food processing industry is one of the most complex manufacturing environments in terms of decision-making, production scheduling, and maintaining food safety [1]. Each market often demands unique product formulations, which leads to frequent changeovers and cleaning cycles to stay compliant and preserve product integrity [1]. These transitions can significantly impact operational efficiency — in fact, some large-scale plants experience 25–30% OEE losses solely due to cleaning and changeover activities. As product variety increases, so does the complexity of scheduling. Managing this manually can quickly become overwhelming — humans simply cannot evaluate every possible combination or scenario within a large-scale production environment [1]. Inefficient scheduling not only leads to production delays but also wastes resources and reduces throughput. This is where digital simulation and intelligent optimization models can make a substantial difference [1]. By simulating hundreds of potential production sequences, these models identify the most efficient plan, minimizing human error while maintaining compliance and productivity [1].

To achieve this, such systems must consider multiple interdependent factors, including: Market demand and customer-driven priorities, Material availability and supply variability, Operational efficiency, by minimizing cleans while ensuring product safety and regulatory compliance [1].

Beyond scheduling, maintaining food quality and safety is equally crucial — not just for consumer protection but also for public health and economic stability [2]. Traditional methods of food quality assessment, while effective, are often labor-intensive, destructive, and lack transparency or traceability [2]. Recent advancements in deep learning and computer vision now offer digitally intelligent, automated, and cost-effective solutions that enhance the precision, consistency, and speed of food quality monitoring [2]. As reviewed in the study [2], these technologies follow a typical workflow — beginning with data acquisition and preprocessing, followed by model selection, training, and validation. They are increasingly applied across various domains, such as image classification, object detection, image segmentation, and image generation [2]. Moreover, integrating these systems with the Internet of Things (IoT) and digital twin frameworks enables real-time monitoring, predictive maintenance, and proactive control of food processing operations [2]. The broader framework for such digital integration can be visualized through five interconnected modeling layers, linking consumer behavior and production dynamics [1]. Consumer preferences are represented at the sensory and sales levels, while production performance is modeled at the phenomena, unit-operation, and plant levels [1]. Together, these create a unified multi-scale model that connects what customers desire with how factories manufacture — ensuring a smooth flow of information and decisions across both domains [1]. Practical examples such as cream cheese fermentation and meat freezing demonstrate how these multi-layered models can guide decision-making in real industrial contexts as shown in the study [1]. While challenges remain in collecting and synchronizing data across different scales, the integration of simulation, IoT, and deep learning technologies shows tremendous potential to drive economic efficiency, food safety, and sustainable growth within the food processing industry [1,2]. This review contributes by establishing a structured framework that integrates digital twin modeling with intelligent scheduling to enhance decision-making, production efficiency, and food safety in a very

complex environment. The proposed integration lays the framework across the industry hence therefore it bridges cognitive scheduling approaches and digital twin frameworks, highlighting how human decision-making and digital modeling can be integrated to improve production reliability, reduce changeovers, and support data-driven operations in complex food processing environments.

Keywords: food processing industry, production scheduling, digital simulation, optimization models, food safety compliance, changeovers, cleaning cycles, Overall Equipment Effectiveness (OEE), digital twin, Internet of Things (IoT), deep learning, computer vision, multi-scale modeling, consumer behavior, unit-operation modeling, sustainable production.

1. Introduction -

This study explicitly explains how important digitization is in the food industry. Digitization of a process/system in any organization is usually performed to make production faster, more efficient, and higher in quality without the possibility of needing new physical equipment [1]. This study categorizes the implementation of the digital models at three different levels explained as follows.

Digital Model - A digital model is the most basic model of simulation that replicates the 1:1 process of a real machine or process or the system in its entirety. The models are generated using historical data/trends and any available production data. The model generated should be as accurate as possible and should be checked and validated to ensure the data used as an input does not have any noise involved in it [1, Table 1].

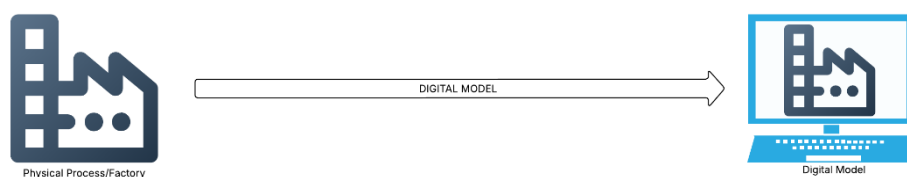


Fig 1. Digital Model Interface [1]

Digital Shadow - A digital shadow is a uni-directional flow from plant to the system. The systems and machines have IOT (Internet Of Things) sensors that track real-time machine data like temperatures, pressures, flow-rates, tank levels etc. The major difference between Digital Model and Digital Shadow is that Digital Shadow will use the real time data to continuously update the outcomes of analysis [1, Table 1].

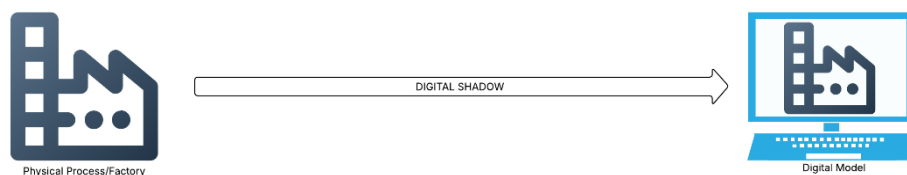
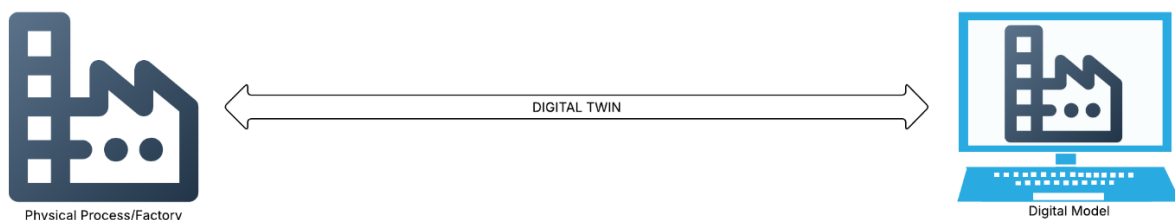


Fig 2. Digital Shadow Interface [1]

Digital Twin - A Digital twin is the most sophisticated system of them all, as it maintains a two-way data flow to and from the system to model. This system acts as an intelligent system as it will simulate and predict the performance in real time and based on the analysis the models will give feedback to the machine/system to update the process accordingly [1, Table 1].

Table 1: Comparison of Digital Model, Digital Shadow, and Full Digital Twin.

Type	Data Flow	Connection	Function
Digital Model	None (offline)	Disconnected	Predict using past data
Digital Shadow	One-way (plant → model)	Semi-connected	Monitor and predict
Full Digital Twin	Two-way (plant ↔ model)	Fully connected	Predict + control

**Fig 3. Digital Twin Interface [1]**

With a detailed understanding of multiple digital models it is really important to understand the scheduling part which is reviewed in the study - The study Analyzing scheduling in the food-processing industry: structure and tasks Here we try to check how would we integrate the digital simulation models with upcoming production schedules specially when it comes to food industries as it includes significant numbers of formulation changes and their respective cleans/washes [3]. The study focuses on how usually the factories oversimplify the scheduling scenarios and avoid considering any dynamic and complex realities as there are multiple factors that will impact real life complex scenarios like material rejections, organizational issues, human judgement error and communication/information flow etc. This study tries to recognise structural and task analysis such that one helps with understanding production requirements, its multiple stages, the equipments involved etc and the other helps understanding the scheduling process, major constraints that needs to be identified so that the model can be generated and help fill out the gap that an individual might miss out on when manually generating the production schedule [3].

By integrating two different methods (structural and Task) the study aims to describe and help structure real

life scheduling problems in food industries, provide a detailed foundation for applying the scheduling methods (existing), and fill the missing gaps [3]. These are a few additional special factors that impact food industries -

- **Perishability.**
- **Variable demands due to constantly changing forecasts.**
- **Complex production chains (mixing, batch production, constant flow monitoring).**
- **High quality and safety demands due to the critical nature of the business.**

The paper demonstrates an example on how to combine the structural and task decompositions (context-based scheduling analysis methodologies) which we can integrate in the model simulation for standardization purposes. The Digital models we generate will use the same proof of concept presented in the paper so that the model can implement and autocorrect itself if there are multiple complex scenarios based on the range of SKUs and multiple types of cleanings included. The integration of the two methodologies brings multiple

benefits and sustainability of the digital model - Algorithmic support for sub-tasks, Evaluation of organizational responsibilities (What is the flow of tasks, who is responsible to perform the process in the flow at every step, etc. Defines every step), Improved information structure and brings more visibility to the system [3].

The main goal of this review is to bring together existing research and practical insights on how this technology of digital models and scheduling frameworks can work together with the food processing industry. The study focuses on how this integration can be achieved and potentially help with improving production reliability,

reduction in changeovers and help strengthen decision making in factories that deal with multiple SKU's and formulation changes causing frequent cleans between Production runs.

Overall the review aims to highlight the opportunity and potential directions for gradually integrating these digital systems into real manufacturing environments to support more efficient and data-driven operations.

Following is the Schematic representation of context-based approach to analyse scheduling problems as used and represented in article Analyzing scheduling in the food-processing industry: structure and tasks [3].

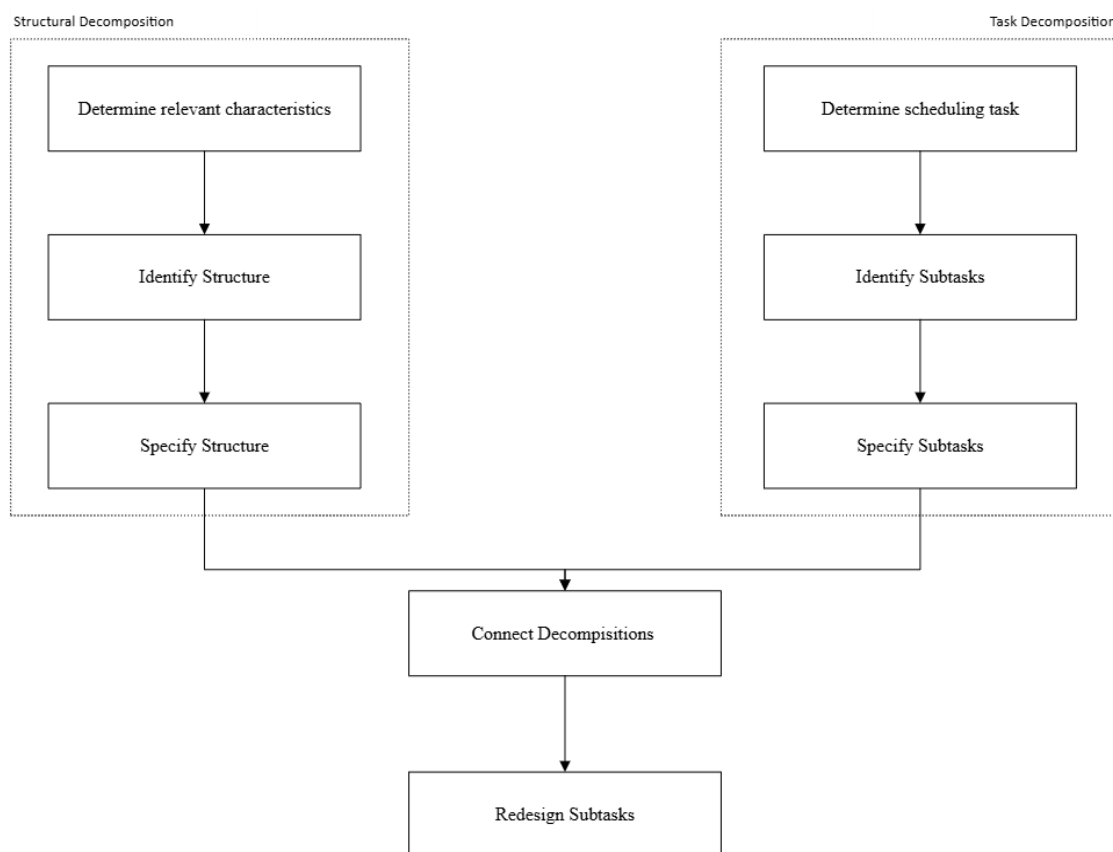


Figure 4. Schematic representation of context-based approach to analyse scheduling problems [3]

2. Methodology - In this review we explore opportunities to improve production efficiency and make the system more reliable by adding stability to the process due to multitude of cleanings and SKUs for the plethora of markets. This framework builds on established methodologies from recent literature and is structured into three core phases - Phase 1. Contextual Analysis: Phase 2 - Multi-Layer Digital Twin Design : Phase 3 - Model Implementation and system integration. [1,2,3,5].

2.1. PHASE 1 - Contextual Analysis.

This phase focuses on understanding the system, the structure, in this case the food production unit. We try to understand the process flow, operators' reaction, their decision making and defining the parameters/constraints to ensure the system is realistic.

2.1.1. Structural Decomposition -

Author in article [3] defines that structural decomposition is highly valuable as it will be responsible for defining and identifying major process characteristics like sequences (this include process sequences and also sequences of formulations based on their cleans), shelf life of the materials, shared resources, warehouse space constraints. The process will be described using process routings, decoupling points, and capacity groups to divide the production system into manageable subsystems and define the flow of materials and operations [3, Fig.1].

2.1.2. Task Decomposition -

Based on the study - Analyzing scheduling in the food-processing industry: structure and tasks [3] this step will study the decision making behaviour of the planners and operators through data observations and trends. This approach suggested by the study will be applied to capture cognitive scheduling strategies, including sequencing logic, constraint handling, and exception management. These insights will later inform which decisions can be digitally supported or automated This study's proposed approach will be utilized to document cognitive scheduling strategies, encompassing sequencing logic, constraint management, and exception handling. The knowledge gained will subsequently guide decisions regarding digital support or automation [3, Fig.1].

2.1.3. Defining Digital Scope -

The initial implementation will begin with a digital shadow and will eventually evolve into a full digital twin depending on the infrastructure setup at the food production facility.

2.2. PHASE 2 - Multi-Layer Digital Twin Design.

The design in this review will be following the similar five-layer framework proposed by article [1] to ensure all the aspects of the business are covered.

2.2.1. Consumer Sales/Forecast Layer -

This layer is important to be recognized and included as it will integrate market data, demand forecasts to get an idea of production needed resulting in their respective scheduling decisions. We integrate this

data based on our last few years of production runs (What was produced, when was produced and what is a set frequency for a certain specific SKUs/markets).

2.2.2. Plant Layer -

At this layer we will feed the models with the data that is relevant to resources allocations, production sequencing, plant capabilities, etc. This data can be extracted from the ERP system and equipment itself [3].

2.2.3. Operations Layer -

This layer will include all the equipment efficiencies, process times, production rates, yield rates, process capabilities such that the model follows the preceding and post activities in terms of equipment [1].

2.2.4. Phenomena Layer -

This layer will include all the material specifications for the food materials, enzymes, products stability tests etc. The purpose of this layer is to incorporate and translate all the necessary measurable process variables to check if anything goes out of spec and is rejected/accepted based on its qualified/approved limits [1].

2.2.5. Sensory Layer -

This layer converts consumer sensory attributes such as taste, color, and texture into quantifiable digital metrics. Deep learning-based computer vision tools which will help support automated visual quality assessment [1, 2].

2.3. PHASE 3 - Model Implementation and system integration.

With completion of Phase 1 and 2 we should have a good robust system that provide a simulation based analysis of what could be the outcomes based on current data/parameters however it will not be able to provide a feedback and in order to achieve that study [2] suggests to integrate simulation models such that the system will integrate with IOT and recognize the realtime data outcome. Each model will be trained on

representative product images and process data, validated using split datasets (training, validation, and test sets).

These generated models will evaluate multiple statistical metrics such as accuracy, precision, recall, RMSE (Root

Mean Square Error). These validated models will be implemented in real-time production systems and its integration with these systems will help complete the loop of digital shadow to develop a digital simulation of the system.

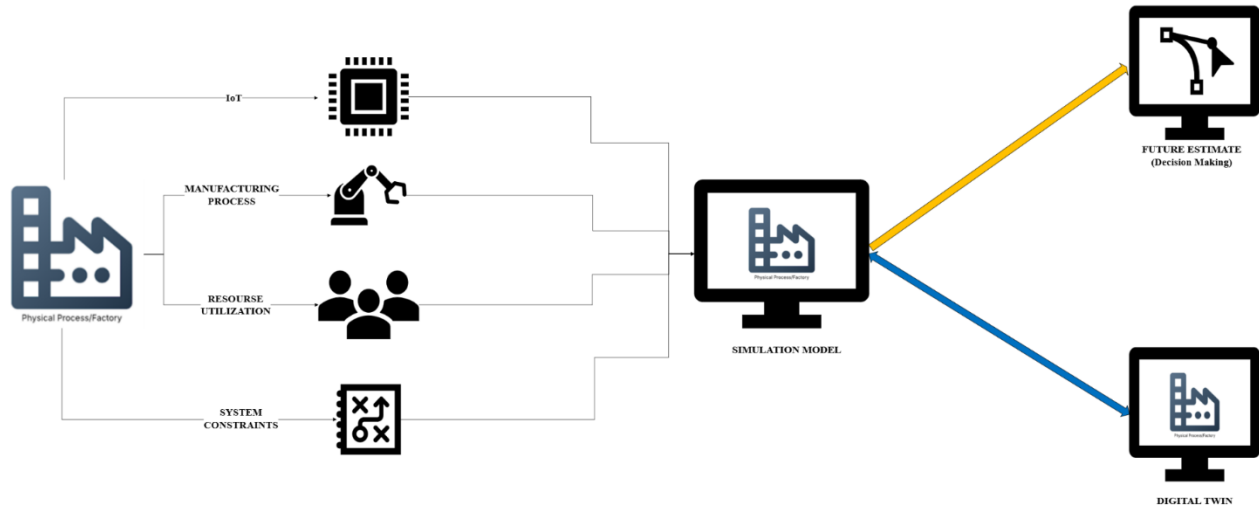


Figure 5. Schematic representation of Digital Twin and Digital Simulation Integration [1]

Based on the above representation it is evident how our model will integrate together when deployed and will include five important steps before deployment of our model refer Fig 6.

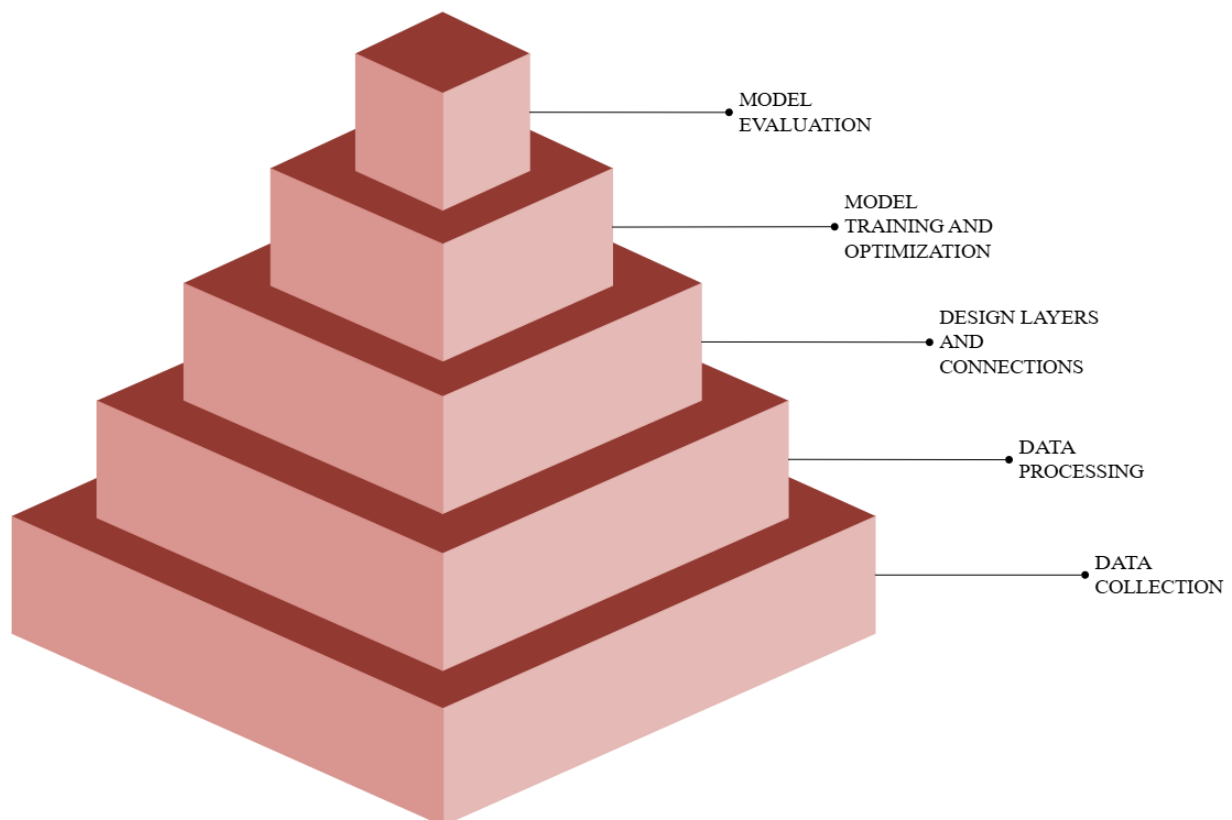


Figure 6. Workflow representation for Digital Twin Simulation deployment [2]

By following the steps individually from bottom to top we will be able to successfully integrate the model such that it will achieve the desired results for providing a detailed analysis and making desired adjustments in order to optimize the process. All the steps are very critical for successful deployment of the model implementation and system integration. Data collection will help us understand the system, its constraints and its limitations based on these data points we process/filter the noise and design layers and connection points, model will train on these layers and based on data and final step will be evaluation of the data to check its accuracy and verifying that the model behaves very close to real processes [2].

3. Conclusion - The integration of digital twin technology in this industry will represent a transformative leap towards smart, more sustainable and data-driven production system. This review demonstrates that by leveraging digital models, digital shadows and full fledged digital models manufactures can move from reactive decision-making to predictive and autonomous operations. Integration of simulation IoT and AI driven approach enables real time understanding of complex manufacturing industries like food industries which includes multiple cleaning cycles, formulation changes and production sequences. This approach will be helpful in optimizing and enhancing the throughput. The contextual and task-based scheduling framework [3] further complements the digital twin design by capturing both the structural characteristics of production and the human decision-making logic that drives it. This dual approach ensures that the developed models are not only technically accurate but also operationally realistic, supporting the planners' cognitive strategies while minimizing errors and communication delays. When integrated across the proposed five-layer architecture — from consumer preferences to plant-level operations — the digital twin acts as a dynamic bridge that connects market demand with factory performance. As industries continue to face challenges such as perishability, variable demand, and stringent food safety requirements, the adoption of such digital ecosystems will be essential. The convergence of IoT, machine learning, and computer vision offers an unprecedented opportunity to improve product quality monitoring, resource utilization, and scheduling efficiency while ensuring regulatory compliance and sustainability. Combining digital twins with intelligent scheduling looks really

promising. The main benefits are that it can make production more reliable, cut down on time lost during changeovers, and help managers make better decisions because they can test out complex scenarios in a simulation first. However, it's not a perfect solution just yet. There are still some significant challenges, like keeping all the data in sync across different systems, the high cost and complexity of setting up the required IoT infrastructure, and the difficulty of accurately capturing the smaller details or expert strategies that human workers use. Addressing these challenges is essential for guiding future research toward solutions that will ultimately lead to the development of truly smart and resilient food processing systems.

4. Future Scope - Future studies could explore a more systematic evaluation of the observed benefits, limitations, and challenges from existing implementations, effectively forming a dedicated discussion on realistic and practical outcomes. This would allow manufacturers and decision makers to better understand trade-offs, optimize digital twin frameworks for specific production environments, and address bottlenecks in real-time scheduling, data integration, and human-machine collaboration. The integration of Digital twin systems, IoT, and AI-based models shows immense potential in transforming food processing operations, several opportunities for future development remain. Future scope can focus on expanding on intelligence of these models across industry platforms.

4.1. Standardization and Interoperability - In order to make this technology scalable and form a digital ecosystem across plants it is very important to develop the infrastructure to support standardization and inter-connectivity of the systems with the help of IoT.

4.2. Enhanced Human-Machine collaboration - As we develop more autonomous systems we need to keep exploring AI-human collaboration frameworks planners and operations teams can identify the patterns and based on cognitive learnings make faster, data-driven decisions.

4.3. Digital Twin for Supply Chain Sync - Extending the digital twin concepts beyond the plant level into the supply chain could enable real-time coordination between raw material suppliers, processors, distributor

channels and the retailers thus providing an end to end digital representation of the entire supply chain.

5. Reference -

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