10th International Food Operations & Processing Simulation Workshop, 010
21st International Multidisciplinary Modeling & Simulation Multiconference

2724-0355 © 2024 The Authors.
doi: 10.46354/i3m.2024.foodops.010

Defining a Cognitive Digital Twin architecture in food supply chains: the early outcomes of DSS4LCO initiative

Gabriele Pasetti Monizza [1,*], Maryam Mozaffari[1], Simone Fabbrizzi[1], Johann Gamper[1], Oswald Lanz[1] and Dominik T. Matt[1]

[1]Free University of Bozen-Bolzano, piazza Domenicani 3, Bozen-Bolzano, IT-39100, Italy

[*]Corresponding author. Email address: gabriele.pasettimonizza@unibz.it

Abstract

Multi-objective and Artificial Intelligence-enhanced optimization methods support the decision makers in finding solutions within trade-offs and conflicting goals, giving rise to a Cognitive Digital Twin framework, capable of simulating, predicting, and prescribing physical behaviors. The research activities on optimization methods in production systems have mainly focused on optimization of individual, single and convergent optimization goals, leaving disruptive external uncertainties to be investigated, such unpredictable climate or social events influencing food supply chains.

This conceptual paper reports the early outcomes of the "Decision Support System for the Life Cycle Optimization (DSS4LCO)" initiative, which aims at implementing a CDT architecture in food supply chains, able to handle multiple data-sources and conflicting goals under uncertainties, combining a DT framework, a lean, agile, resilient, and green (LARG) index and value stream mapping. Adopting the Design Science Research approach, the essay discusses the first 3 steps of the approach, aiming at identifying the research problem, contextualizing this issue within the existing knowledge base, and proposing a solution for the problem. Results discuss the definition of a CDT architecture, introducing the challenges to be faced in the future developments of the research initiative.

Keywords: Food supply chain; LARG metrics; Digital Twin; Cognitive Digital Twin; Active Learning

1. Introduction

Starting from the digitization of information since the 1990s, and through the universal adoption of digital communication networks (such as internet), industries are migrating their production systems towards smart and interconnected systems, relying on a combination of information, computing, communication, and connectivity technologies. This transformation has been defined as the 4th industrial revolution, or Industry 4.0 (Jopp, 2013). Smart and interconnected systems apply Industrial Internet of Things (IIoT) devices to enable capabilities of coupling physical entities with digital artifacts, shaping the Cyber-Physical Production Systems (CPPSs) as the standard systems within the Industry 4.0 model (Piardi et al., 2020; Tekaat et al., 2021).

Since CCPSs allow the interaction between digital and physical realms, the Digital Twin (DT) framework has been introduced as a comprehensive method to provide a decision support system through a digital counterpart of a physical entity. Thanks to multi-objective and Artificial Intelligence (AI)-enhanced optimization methods, a DT may increase its capabilities of simulating, predicting, and prescribing physical behaviors, towards a Cognitive Digital Twin (CDT) framework (Fernández et al., 2019).

Applications of optimization methods in production systems showed a great potential for improving reliability of decision support systems, especially for individual - avoiding conflicting, single and convergent optimization goals like cost-efficiency (Lean) or sustainability (Green). The potential of these methods remains unclear under external uncertainties or disruptive events, such as unpredictable climate or social events that may lead to overproduction or supply shortages. These events require a fast reaction and adaptation of supply chains to avoid wastes of resources or interruptions (Guidani et al., 2024), especially in supply chains that rely on unpredictable natural resources like in food production or renewable-energy production.

The "Decision Support System for the Life Cycle Optimization (DSS4LCO)" initiative aims at implementing a CDT architecture in food supply chains, to investigate potentials of multi-objective optimization methods, under external uncertainties or disruptive events. Combining a DT framework, a lean, agile, resilient, and green (LARG) index, and the value stream mapping technique, the research initiative will develop a prototype of a CDT and generalize the outcomes through an applied approach, adopting the Design Science Research (DSR) approach.

This conceptual paper discusses the first three steps of the adopted DSR approach: (step 1) identifying the research problem, (step 2) contextualizing it, and (step 3) proposing a solution, outlining the challenges to be addressed in the following steps. Section 2 introduces a comprehensive literature review about DT frameworks, CDT frameworks and decision-making support systems. Section 3 shows the adopted methods: (1) introducing the DSR approach, (2) defining the scope of the initiative and the general research questions, (3) identifying the gaps in the literature and (4) defining a CDT architecture. Section 4 provides an insight of early results, discussing the challenges to be addressed in the future developments of the research initiative.

2. State of the art

2.1. Digital Twins in industrial applications

According to Grieves (2014), the concept of DT was introduced at University of Michigan in 2003 to identify a digital representation of a physical product based on three main parts: (i) the physical product in the real space, (ii) the virtual product in the digital (or virtual) space, and (iii) the connection of data and information that connects the real and the virtual products.

Over the last two decades, the first concept of DT has evolved towards a comprehensive framework to represent not only products, but also entire systems (Hsu et al., 2019). Since CPPSs apply cyber-physical systems to enhance smart interaction capabilities through IIoT devices (Piardi et al., 2020; Tekaat et al., 2021), the connection of data and information is demanded to each single device, and the DT becomes the digital model of the physical system in a one-to-many relationship (Hsu et al., 2019). Within this framework, the combination of IIoT devices and a DT model can be considered as a cyber-physical system itself, and it can be described through the 5C taxonomy proposed by Bagheri et al. (2015).

The definitions of cyber-physical systems outlined by the scientific community (Piardi et al., 2020; Tekaat et al., 2021), are converging towards a definition of systems for industrial applications with cognitive and self-configuration capabilities. These capabilities can be delivered through a deep understanding of the physical systems where the device is deployed. In industrial applications, the deep understanding implies that the IIoT device should collect information about his own tasks and relate theses information to the physical system. In other words, the device should be able not only to apply Connection and Conversion layers of the 5C taxonomy but also to interact with a digital model of the physical system to effectively apply Cognition and Configuration layers.

The 5C taxonomy aims at describing the a priori capabilities of a system but neglects the potentials that may arise in real applications. As discussed by several authors, a DT may enhance the performance and the efficiency of CPPSs by enabling different capabilities: multi-physics simulations (West & Blackburn, 2017), visualization of a physical entity (Douthwaite et al., 2021) and the ability of proactive state predictions for understanding the remaining life of a system (Eyre & Scott, 2020). Thus, focusing on the creation and the structure of a DT, Bonney et al. (2022) introduce a description through three different layers:

- **Internet-of-things layer** - This layer leads the interaction between the physical domain and the digital realm, applying IIoT devices such as sensors, control hardware, and actuators.
- **Interface layer** - It manages the execution of tasks and workflows, applying the information collected by the previous layer. It also facilitates the communication between different network services.
- **Cloud computing layer** - It hosts network services like cloud data storage, high-performance computing, and other remote components connected to the DT. These services improve both physical and digital systems by offering additional network-based capabilities.

A DT, as, a digital copy of its physical counterpart not only offers a real-time access to the data coming from the physical domain, but it also allows to analyze, simulate changes, and improve the physical counterpart itself.

2.2. Digital Twins applications in food production

In food production industry, the peculiarities of DT frameworks offer the opportunity of overcoming the fundamental challenges in food supply chains, such as: quality assurance, waste reduction, safety, and security management (Casino et al., 2021; Pylianidis et al., 2021). Huang et al. (2024), through a systematic literature review, define a DT implementation process of five steps divided into three different stages. They aim at addressing not only the fundamental challenges, but also arising challenges, such as preventing supply shortages or managing short product-shelf-life (La Scalia et al., 2016). Besides expecting several benefits from the implementation of DT frameworks, their outcomes define five recommendations for future research activities:

1. Defining evaluation metrics and performance indicators.
2. Providing standards and improving scalability of IIoT devices for facilitate implementation at Internet-of-things layer.
3. Extending the application of DT frameworks across the whole food supply chain instead on single stages.
4. Providing consistent analysis of user acceptance of the technologies involved.
5. Evaluating how DT frameworks can support a wider digital transformation of the food production industry.

Singh et al. (2023) investigate the factors behind the adoption of DT in food supply chains for enchaining resilience and sustainability, and they try to analyze the causal relationship among the factors through a grey causal modelling approach. They identify 15 factors through an extensive literature review: Risk Assessment, Quality, Bullwhip Effect, Flexibility, Coordination, Efficiency, precision farming, Safety, Visibility, Traceability, Logistics capabilities, cold chain facilities, food security, Governance, and weather forecasting. The results of their casual magnitude analysis highlight that DT frameworks improve stakeholder coordination, boosts visibility in the food supply chain, thereby mitigating risks and enhancing efficiency. Resilience hinges on flexibility and robustness, ensuring the smooth flow of high-quality goods and fostering societal benefits while upholding sustainability. Consequently, adaptability and flexibility positively impact both sustainability and resilience.

Valero et al. (2023) propose a new DT framework applying dynamically optimized distribution to improve the resilience of interconnected and interdependent food supply chains against unforeseen changes. Through a case study in the UK, they estimate savings of more than £25,000 and 150 tons of CO2 per shipment in a standard refrigeration unit.

Tan et al. (2023) apply DT frameworks to control ventilation in indoor food court for assessing and managing resilience in real-time, against indoor transmission of airborne infectious disease. They show that such solution result in enhancements in the duration of disruptions, resilience loss, and the average recovery rate for patrons in a food court.

DT frameworks can be successfully applied for reducing the energy demand without impacting the productivity or the quality of deliveries in food supply chains. Li et al. (2024) introduces DT frameworks to evaluate and optimize the performances of cascade refrigeration systems. Relying on simulations based on AI-enhanced analysis of real-time data, their DT framework increases the overall performance of refrigerators by 9.1% and reduces the total energy demand of compressors up to 13.1%. Similarly, Büchele et al. (2024) apply DT frameworks to apple storage facilities, saving energy demand through a real-time control of storage temperatures. They highlight that, beyond energy savings, DT frameworks increase the economic efficiency by reducing food losses and wastes.

Ding et al. (2023), by developing a review of the actual stage of Industry 4.0 technologies applied to the food industry, identify the integration of multiple data sources in intelligent digital models as possible direction for innovation and improvements. Such intelligent data models may provide a more comprehensive information management and a more reliable analysis of results, enhancing the awareness of the decision makers.

Guidani et al. (2024) introduce a novel Agri-Food Supply Chain DT, relying on an integrated, flexible, and holistic framework from field to customer. The proposed framework aims at filling a gap of a multi-dimensional performance assessment in DT frameworks applied to food supply chains, as highlighted by Yadav et al. (2022). Their results overcome the limits of heterogeneous traceability architectures, offering an architecture able to process and assess overall impacts and externalities of food supply chains. Such architecture improves the transparency and the shared visibility of operation and processes along food supply chains, enhancing the awareness of both decision makers and customers.

2.3. Towards a Cognitive Digital Twin

AS showed by applications in the previous section, since DT frameworks are real-time representations of physical entities, they improve situational awareness for observability, controllability and decision-making. Situational awareness implies a continuous and mutual interaction between humans and DT frameworks. Fernández et al. (2019) leverage on this aspect comparing the DT frameworks with symbiotic autonomous systems. These systems foster the convergence of human and machine augmentation, towards hybrid human-machine systems. Thus, they highlight a lack of high-level consciousness capabilities in DT frameworks which limits the symbiotic relationship between humans and these frameworks. To provide consciousness capabilities, they define a Cognitive Digital Twin (CDT) as:

> a digital expert or copilot, which can learn and evolve, and that integrates different sources of information for the considered purpose (Fernández et al., 2019).

Relying on exiting definitions, Zheng et al. (2022) derive a comprehensive definition of a CDT through five common elements and features:

1. **DT-based** – A CDT is an augmented version of DT, including all the capabilities of the 5C taxonomy (Bagheri et al., 2015) and relying on a three-layer structure (Bonney et al., 2022).
2. **Cognition capability** - A CDT implements semantic technologies, AI-enhanced methods, and IIoT devices to recognize complex and unpredictable events, applying optimization strategies in real-time.
3. **Full lifecycle management** - A CTD includes all the different digital models across the entire lifecycle of a system, likewise a DT framework in food production should cover the whole food supply chain (Huang et al., 2024).
4. **Autonomy capability** - A CDT operates without human assistance or limiting human intervention.
5. **Continuous evolving** - A CDT embodies learning and evolving capabilities by autonomous or human-assisted features.

Their comprehensive definition of a CDT has not to be intended as a replacement of the DT frameworks, but it acts as an extension, envisaging the CDT as a federated version of a DT framework. Such federated version requires a more complex architecture than a DT. Thus, they outline a reference architecture based on RAMI 4.0 (Schweichhart, 2016) identifying several enabling technologies in different areas:

- **Semantic technologies**
  - Ontology engineering
  - Knowledge graph
- **Model-based system engineering**
- **Product lifecycle management**
- **Industrial data management technologies**
  - Cloud/Fog/Edge computing
  - Natural language processing
  - Distributed ledger technology

Ali et al. (2024) offer a systematic literature review in the realm of Industry 4.0/5,0 about cognitive systems and cognitive interoperability. Beyond the potentials of cognitive systems towards a resilient, sustainable and inclusive industry, they highlight several challenges to be addressed. Combining static and dynamic features, cognitive systems may lead to complexities for coordinating different components in real-time environments, since an interoperability standard is still missing. Furthermore, much effort is required to provide a deep understanding of hybrid human-machine systems, especially through applications in real case studies aiming at analyzing the symbiosis of humans and machines.

Since the CDT is an emerging concept, it requires new strategies and policymakers' support for facilitating the transformation of industries towards more resilient, sustainable, and inclusive industry models, especially implementing the United Nations' Sustainable Development Goal 9 (Sharma & Gupta, 2024). The lack of transformation strategies and policymakers support inhibits applications in real case-studies, which are limited to ongoing research projects or explorations of DT frameworks just integrating AI components, according to Zheng et al. (2022) and Ali et al. (2024). As of May 2024, SCOPUS database is not returning any record about CDT in food production - query formula: TITLE-ABS-KEY ("cognitive digital twin" AND "food").

2.4. Handling conflicting goals in decision-making support systems

Concerning the recommendations 1 and 3 identified by Huang et al. (2024) in Section 2.2, the definition of metrics and performance indicators for food supply chains is a complex task, especially aiming at a comprehensive and holistic representation of a whole supply chain (Guidani et al., 2024).

A metric index for production systems should adopt performance indicators aligned with production goals, implementing parameters adaptable to strategic market goals. Intrinsically, every production system must deal with four main goals (variability, quality, economy, and speed) which are structured in a conflict relationships model of goals compatibility, goals subordination, and goals antagonism (Erlach, 2013). These conflicts imply that it's not possible to fulfill all goals simultaneously, and optimization strategies must deal with trade-offs.

Since the conflict relationships model proposed by Erlach (2013) is mainly focusing on the goals domain of Lean manufacturing, it is mostly correlated to the production and transformation stages within a supply chain. Extending the goals domain to all the stages of a supply chain means including other domains, in the attempt of providing an efficient and effective flow of materials and information among the whole supply chain (Carvalho et al., 2011). For this purpose, Azevedo et al. (2011) propose the LARG index as a combination of four goals domains: Lean, Agile, Resilient, and Green. The proposed index exponentially increases the conflict relationship of goals, since some domains are contradictory at strategic and tactical level, such as Lean and Resilient in managing warehouse stocks.

Several authors are investigating the possible implementation of the LARG index in different industrial sectors, highlighting the potential to generate great advantages for companies, and recommending the use of digital technologies to: (i) facilitate the data collection through IIoT devices and (ii) provide assisted decision-making systems

(Khanzadi et al., 2024).

Bottani et al. (2022) introduce LARG index for evaluating food supply chain performances, proposing a framework of 13 performance indicators. They remark that more effort is required to validate the proposed framework through real case studies, supporting decision makers in figuring out the best combination of performance indicators.

Sahu et al. (2023) outline a decision-making framework for selecting suppliers of an automotive supply chain in India. Identifying more than 60 performance indicators within the LARG index, they implemented a multi-objective optimization method to select the optimal supplier, providing a real case study with tangible feedback using experts' and stakeholders' contributions.

Optimization tasks of contradictory goals, such as in the LARG index, demand multi-objective optimization methods supporting a multi-criteria decision-making system. Contradictory goals lead towards a set of alternative solutions, called Pareto optimal solutions. In multi-objective optimization, finding the optimal solution among Pareto optimal ones should not be intended as finding a unique solution, but as offering a plethora of trade-off solutions. Thus, multi-objective optimization methods should provide: (i) a set of solutions from the Pareto-optimal front and (ii) a set of solutions representing the entire range of the Pareto-optimal front. Since multiple optimal solutions and trade-offs are provided, selecting the best solution becomes a very complex task, requiring high-level information and experience-driven consciousness (Branke et al., 2008).

In the last 20 years, several authors have discussed the implementation of AI methods (such as Machine Learning) to multi-objective optimization, aiming at providing autonomous decision-making support systems. A brief search in SCOPUS database returns more than 200 records - query formula: TITLE-ABS-KEY ("multiobjective optimization" AND "decision making" AND "machine learning").

Focusing on the most recent records, Wang et al. (2022) propose a multicriteria decision making framework of 7 steps, applying a machine learning aided multi-objective optimization method. Through two applications in chemical engineering, they aim at increasing the energy content and reduce the greenhouse emission of supercritical water gasification process without relying on decision makers' feedback.

To better distribute a set of solutions on the Pareto-optimal front, Deb et al. (2023) train machine learning algorithms to improve outputs from evolutionary multi-objective optimization algorithms without additional optimizations, providing a proof-of-concept of machine learning methods in aided multi-objective optimization. Similarly, Nabavi et al. (2023) reduce from two days to one minute the multi-objective optimization of thermal cracking process, relying on deep learning techniques in olefines production industry. As well, Hoang et al. (2022) apply a hypernetwork within a Pareto-front learning framework, to improve the generation of trade-offs among the pareto front. Through different experiments, they measure that a multi-objective optimization machine-learning algorithm provide better performances in comparison to baseline Pareto-front learning frameworks.

Mousavi et al. (2023) develop an algorithm in business analytics to improve sustainability and resiliency of companies, combining multi-objective optimization and machine learning. Through three industrial case studies which directly involve decision makers, they algorithm outperforms non-interactive ones by providing more reliable solutions.

Hu and You (2024) propose a CDT framework (under the definition of cyber-physical-biological system) for smart energy management in hydroponic plant harvesting. Implementing physics-informed deep learning techniques upon multi-objective optimization algorithms, they measure a reduction of energy expenditure of 8.75%, and a considerable reduction in computational time, lending towards a real-time capability in decision-making support systems.

3. Materials and Method

The authors report the early outcomes of the "Decision Support System for the Life Cycle Optimization (DSS4LCO)" initiative, which aims at implementing a CDT architecture in food supply chains through the development of a case study, involving practitioners and decision makers. The research initiative adopts the Design Science Research (DSR) approach which aims at developing new artifacts through:

> a knowledge-based design process for solving problems relevant to practice (Hevner et al., 2004).

In their definition, the artifact is an outcome of research activities to outline and evaluate a new methodology, a new technology or even a new product.

The DSR approach is structured among 7 main steps which apply reproducible methods:

- Step 1 - Identifying a problem relevant for practical tasks, with potentials for scientific contributions.
- Step 2 - Contextualizing the problem within the existing knowledge base (e.g. scientific literature).
- Step 3 - Formulating a possible solution with potential of filling the gaps within the scientific literature.
- Step 4 - Implementing the solution in a case-study prototype.
- Step 5 - Demonstrating the utility of the proposed

solution through a validation step involving relevant stakeholders.
- Step 6 - Generalizing the outcomes of the previous steps.
- Step 7 - Assessing possible extensions and further applications of the proposed solution.

At the actual stage, the DSS4LCO initiative completed the first three DSR steps, towards the definition of a CDT architecture implementing a multi-criteria decision-making support system. The following sections discuss the scope of the DSS4LCO initiative (DRS - Step 1), the identified gaps (DSR - Step 2) and the definition of a CDT architecture that will be implemented in the next DRS steps (DSR - Step 3).

3.1. Scope of the DSS4LCO initiative

Food supply chains are facing several fundamentals challenges, dealing with UN Sustainable Development Goals (SDGs), to: achieve food security (SDG 2), ensure healthy life (SDG 3), ensure availability of water (SDG 6), promote economic growth (SDG 8), build resilient industrial infrastructure (SDG 9), ensure sustainable consumption and production patterns (SDG 12), combat climate change (SDG 13), promote sustainable use of terrestrial ecosystems (SDG 15). Such a wide framework of goals requires transdisciplinary high-level decision-making capabilities.

As discussed in Section 2.2, DT frameworks can effectively support decision makers in handling complex managing tasks towards more efficient and more effective management of food supply chains. Since the DT frameworks improve the situational awareness of decision makers, they aim at acting as a symbiotic system, relying on a continuous and mutual interaction with humans. However, as discussed in Section 2.3, a lack of high-level consciousness is limiting the autonomous capabilities of the DT frameworks in decision-making tasks, and an evolution towards more conscious systems is required.

Considering the novelty of the CDT topic (Section 2.3), the DSS4LCO initiative explores the application of CDT frameworks in food supply chains by defining a CDT architecture to provide a comprehensive and autonomous decision-making support system. Through the validation of such defined architecture, the research initiative tries to provide an answer to the following research questions:

- RQ 1 - How should a CDT architecture be structured for food supply chains?
- RQ 2 - Which metric indexes could provide a comprehensive and reliable framework for evaluating the performances of food supply chains?
- RQ 3 - How to include multiple data sources, even external, to increase the conscious capability of a CDT framework within food supply chains?
- RQ 4 - Can CDT frameworks autonomously handle uncertainties and disruptive events without human assistance or limiting human intervention?

3.2. Identified gaps

The research questions introduced in the previous section aim at filling some of the gaps identified in the scientific literature among Sections 2.2, 2.3, and 2.4.

The RQ1 would provide a definition of a comprehensive CDT framework for food supply chains. According to the recommendations of Huang et al. (2024), future research activities should extend the application of DT frameworks (and then of CDT frameworks) across the whole food supply chain. This extension should lead towards a more comprehensive framework able to handle multiple data sources, even external, enhancing the awareness of the decision makers. Several authors (Section 2.2) investigate DT applications in food supply chains, but only Guidani et al. (2024) try to extend the framework towards a holistic framework from field to customer, dealing even with externalities. However, their study is still focusing on DT frameworks without arguing on high-level cognitive capabilities for autonomous decision-making tasks. Nowadays, applications of CDT frameworks and the definition of a comprehensive CDT framework in food supply chains seems an unexplored topic (Section 2.3).

The RQ2 deals with the definition of comprehensive metric indexes in DT/CDT frameworks for evaluating the performances of food supply chains. Since research activities on metrics are recommended (Huang et al., 2024), several authors are offering specific metrics in their application of DT frameworks (Section 2.2). However, these metrics are limited to convergent goals (without conflicts), limiting the optimization of performance indicators to specific goals domains, such as: resilience in logistics (Valero et al., 2023), resilience in production (Tan et al., 2023), or energy efficiency in storage facilities (Büchele et al., 2024; Wang et al., 2022). Even if comprehensive metric indexes are available, such as the LARG index (Section 2.4), there is a lack of applications in real case study within food supply chains (Bottani et al., 2022) and the combination of these indexes with DT/CDT frameworks must be investigated.

Comprehensive metric indexes imply handling multiple optimal solutions and trade-offs since goals domains are structured in a conflict relationships model of goals compatibility. As highlighted by Branke et al. (2008), multi-objective optimization tasks require a reliable model of the problem to be optimized, and the selection of the solution require high-level information and experience-driven consciousness. In the realm of DT/CDT frameworks this consciousness must be transferred to autonomous decision-making systems to improve the symbiotic situational awareness of humans and DT frameworks

(Fernández et al., 2019). The RQ3 faces the challenge of transferring the conscious capabilities of humans to a CDT framework, applying the enabling technologies identified by Zheng et al. (2022). The application of cognitive capabilities showed by Hu and You (2024) is limited to a convergent goal, such energy efficiency. Thus, comprehensive system models and holistic semantic descriptions, relying even on external data, need to be enhanced in food supply chain applications.

Since applications of CDT frameworks in food supply chains seems an unexplored topic, the RQ4 aims at understanding if and under which conditions a CDT framework can provide a multi-criteria autonomous decision-making system. As discussed in sections 2.2, 2.3, and 2.4 the literature referred to food supply chains is showing great potentials and benefits, but it is not contributing to a clear understanding since it is lacking a holistic combination of all the topics involved. Applications of DT frameworks are lacking handling multiple optimal solutions and trade-offs, without applying comprehensive metric indexes, or they are lacking autonomous capabilities, without exploring the symbiotic situational awareness of humans and DT frameworks, under uncertainties or disruptive events. Similarly, early applications of CDT frameworks are exploring real-time capability in decision-making support systems, but they a limiting their studies to convergent goals. Other authors are investigating comprehensive metric indexes, such as the LARG index, but they are providing theoretical frameworks which need to be validated and enriched through real case studies.

3.3. Defining a CDT architecture

The DSS4LCO initiative started defining a CDT architecture to answer the research questions introduced in Section 3.1.

Since a reliable model of the system is required to enable cognitive capabilities (Zheng et al., 2022), and to perform multi-objective optimization (Branke et al., 2008), the authors identified the Value Stream Mapping (VSM) as comprehensive model for food supply chains, able to provide a clear description of the relationships and the information among the physical entities.

Formalized by Rother and Shook in 1998 (2003), the VSM produces a blueprint of an entire flow of processes within a supply chain, providing a common language for talking about processes. It shows the linkage between the information flow (in the digital realm) and the material flow (in the physical realm) providing a comprehensive model of a system in a highly effective manner (Erlach, 2013). The flow of processes within a supply chain is represented by the mean of logical connections (the information or material flows) among single-step processes (Figure 1), described adopting a specific legend of symbols, to provide a comprehensive description of the single-step process (Figure 2).

The VSM model can provide several details at single-step level, collecting data gathered by IIoT devices or by users, such as: resources applied, working rates (triggered by actuators or measured by sensors), quality-check data (from sensors), calculated performance indicators (from data measured by sensors), description of managing and control strategies. At overall level, the model delivers a relationship model of the single-step processes, through the representation of the information and the material flows, providing a clear understanding of the interdependencies of the single-step process.

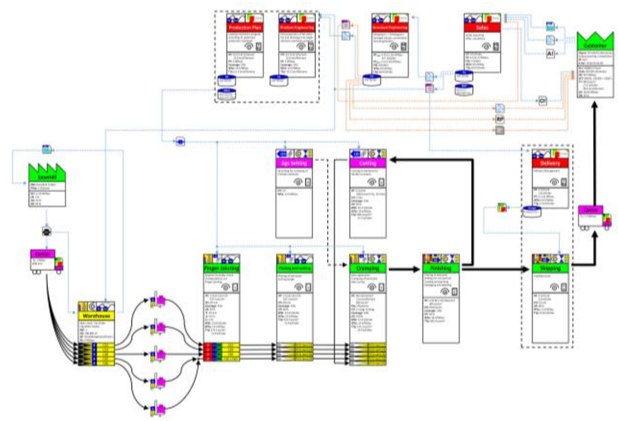

Figure 1. An example of a VSM model - adapted from (Schweizer, 2013).

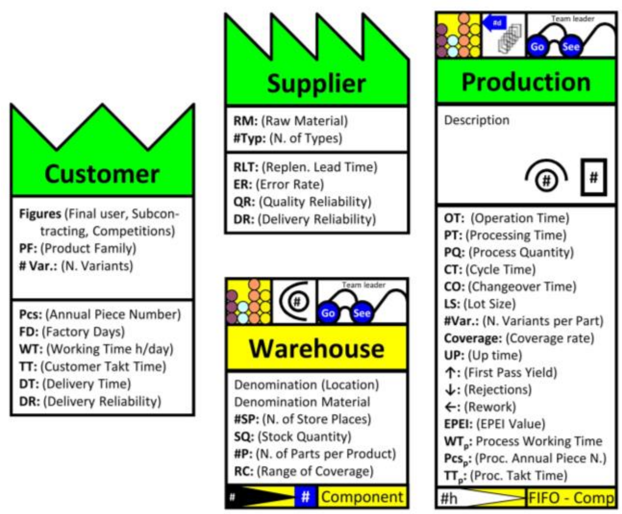

Figure 2. An example of single-step process symbols within a VSM - adapted from (Schweizer, 2013).

Starting from a first iteration between a decision maker and a DT framework, a first model can be established through a snap-mapping method by way of interviews, measuring and counting by human auditors (Erlach, 2013). In a second iteration, the model can be connected to IIoT devices at single-step processes level and it can be connected to a multi-objective optimization engine which aims at finding optimal solutions within a comprehensive metric index, such as the LARG one. This implementation strategy, combined with the VSM peculiarities, establishes a base-line DT framework able to offer: (i) enough flexibility in representation capabilities, (ii) a comprehensive set of performance indicators, and (iii) a detailed semantic description of the real entities. Such defined VSM model provides a reliable model for a symbiotic situational awareness of humans and DT frameworks (Fernández et al., 2019) towards the implementation of cognitive capabilities.

Referring to Zheng et al. (2022), the CDT architecture becomes a federated version of the defined base-line DT framework, distributing the components among two different domains: a DT domain and a CDT domain (Figure 3). The DT domain deals with establishing the connection between the IIoT devices and the multi-objective optimization engine, through a virtual model that relies on the VSM model and on the LARG index.

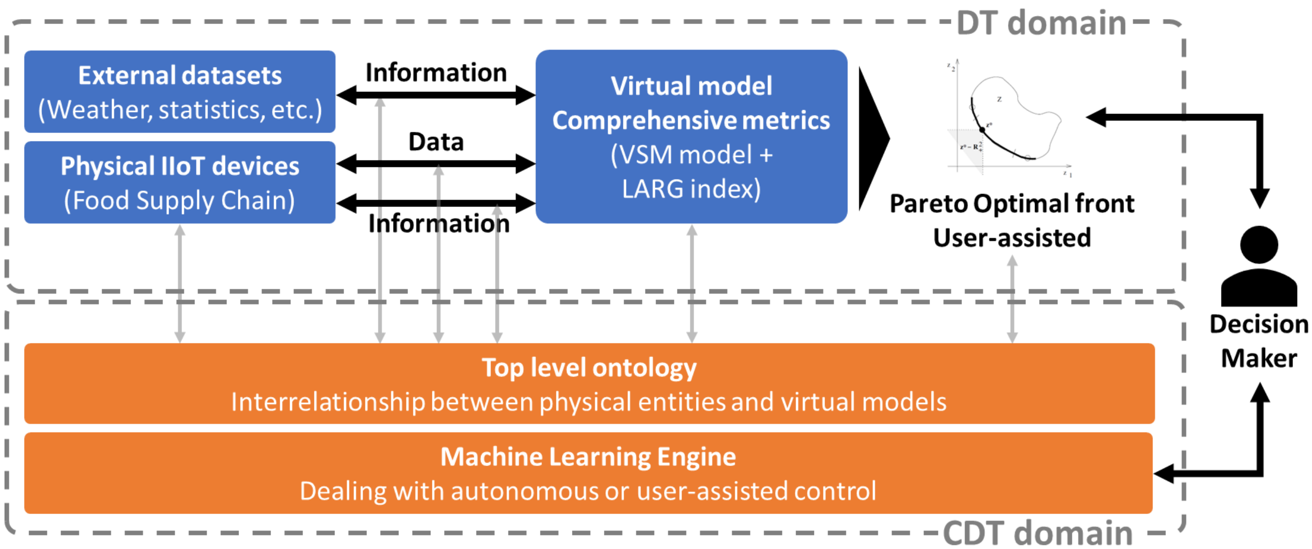

Figure 3. The CDT architecture of the DSS4LCO initiative.

The CDT domain adds cognitive capabilities on top of the DT domain through a top-level ontology and a machine learning engine. Interacting with all the components within the DT domain, the top-level ontology aims at organizing and modelling food data, as well as identifying connections among different components of a food supply chain. Relying on the metadata or schema by the top-level ontology, and on the instances from knowledge graphs, the machine learning engine aims at providing a real-time autonomous decision-making system without human assistance or limiting human intervention.

Within such defined architecture the decision maker interacts at DT domain level defining the VSM model and selecting the optimal solution among the ones delivered by the multi-objective optimization engine. Doing so he provides a semantic description to the top-level ontology within the CDT domain and trains the machine learning engine towards a sufficient level of confidentiality to perform autonomously decision actions.

4. Insights of early results

In the following sections the authors discuss some early results of the research activities within the CDT domain, introducing the main challenges to be addressed during the development of the further steps of the DSR method.

4.1. Defining a top-level ontology

The volume of transdisciplinary and heterogeneous data generated from the food supply chain process exist as information silos, making efficient data exploitation impossible. Therefore, there is a need to organize and integrate food data in the food supply chain. Ontologies and knowledge graphs can provide a standardized conceptual terminology in a structured form and, thus, can effectively organize these food data to benefit various applications (Min et al., 2022). While an ontology is metadata or schema, which represents more complex structures with relationships between a set of concepts, the focus of knowledge graphs is instances. The authors develop an ontology for organizing and modeling food data, as well as identifying connections among different components of a food supply chain.

Food ontologies with an emphasis on health and nutrition can aid in recommending healthy eating habits in various food applications. For example, the HeLiS ontology (Dragoni et al., 2018) intends to give a comprehensive representation of foods, physical activities, good practices, user preferences, and habits to help promote healthy living. HeLiS covers concepts ranging from activities to nutrients in foods, as well as the user concept. This enables the association of certain health-related events with individuals for purposes such as health monitoring or nutritional applications. FoodKG (Haussmann et al., 2019) is a large-scale and integrated knowledge graph that covers recipes, ingredients, nutrients, and food substitutions. This is a valuable resource for assisting users in personalizing their dietary goals and recommending healthier food.

Some food knowledge graphs, such as Foodbar (Zulaika et al., 2018) and RcpKG (Lei et al., 2021), have been mainly developed on recipe entities extracted from recipe-sharing sources (websites, social networks, etc.) to support recipe-related applications.

There are also ontologies that focus on the food safety domain, especially to support food traceability. For example, Food Track & Trace Ontology - FTTO (Pizzuti et al., 2014) was created to aid with food traceability. It incorporates representative food concepts from the supply chain and can integrate and connecting the essential characteristics of the food traceability domain.

Some ontologies are built for specific food categories. For example, the Meat Supply Chain Ontology - MESCO (Pizzuti et al., 2017) extends the FTTO to adapt the meat supply chain area. It supports the management of meat traceability from the farmer to the consumer.

Finally, A global and comprehensive farm-to-fork ontology about food is FoodON (Dooley et al., 2018), which contains raw food source ingredients, food categories and products, as well as process terms for packaging, cooking, and preservation.

There exist not only theoretical studies about food ontologies and knowledge graphs. Several companies, such as Uber, Edamam, BBC, and Yummly, adopted these research results to develop their own customized food ontologies and knowledge graphs to power various products and make them more intelligent from different specific domains. For example, Uber Eats (Hamad et al., 2018) builds on a food knowledge graph to facilitate food-related retrieval and suggestion. Edamam (edamam.com) created a comprehensive knowledge graph on food and cooking, which included recipes, ingredients, nutrition information, measures, and allergies. The goal of this food knowledge graph is to provide consumers with numerous ways of searching, enabling better food choices. Yummly (yummly.com) developed a knowledge graph to offer a semantic web search engine for food, cooking and recipes.

A food supply chain includes all the steps involved in the journey of food items from production to consumption. Globalization has led to longer and more fragmented food supply chains. This poses two main challenges: difficulty in food traceability and increased food waste. Therefore, mapping and connecting different components of a supply chain is critical to achieve reliable food traceability and control food waste. The food ontology and knowledge graph provide an effective approach for modelling, integrating, and aligning food data in food supply chain management. To this end, the DSS4LCO initiative develop an ontology to organize and integrate data related to products, actors and processes involved in the food supply chain with the goal of reducing food waste.

The construction process of the proposed ontology is defined using the Methontology presented by Fernández-López et al. (1997). It is a methodology for ontology development that includes the following activities:

- specification phase: This phase involves identifying the purpose of the ontology, defining the scope and objectives of the ontology, and understanding the domain requirements. In particular, the main goal of our ontology is to support information management and identify connections in different components of the supply chain with the goal of reducing food waste.
- knowledge acquisition phase: This activity employs Different knowledge acquisition approaches to generate an early version of the ontology definition document. for this, an in-depth analysis of the food supply chain is required to identify the relationship between actors and processes.
- conceptualization phase: During the Conceptualization phase, the acquired knowledge is structured into a conceptual model. The identified concepts have been translated into classes, and their attributes have been represented using data properties. The relationships between concepts have been modelled through several object properties.
- implementation phase: The ontology is typically represented using ontology languages such as the Web Ontology Language (OWL), which can be implemented using ontology development tools. During the implementation phase, classes and properties have been organized in taxonomies. Additionally, constraints and restrictions have been defined. We use the Protégé tool, a popular tool for creating and modifying ontologies with graphical representations, to build and implement the proposed ontology.
- validation phase: In this phase, knowledge representation techniques are employed to evaluate incompleteness, inconsistencies, and redundancies of the developed ontology.

4.2. Outlining a machine-learning aided decision-making system

As highlighted in Section 2.3, CDT frameworks are meant to learn and evolve through interaction with the user to sustain the decision-making process.

Given the quantity of data that a DT model could potentially gather (through, for instance, IIoT devices) the usage of machine learning techniques to power its decision-making capabilities seems a reasonable choice.

On the other hand, the continuous interaction of a virtual model with its physical entities, the user, and possibly unpredictable external factors pose some serious threats to the use of data-driven learning technologies in this context. Indeed, changes in distribution of the data or in the business needs could seriously degrade the performance of the underlying automated learning systems making the DT useless at best, dangerous at worst. Therefore, the authors identified two techniques that would help deal with the above-mentioned issues.

First, any automated decision systems should be equipped with appropriate safeguards. For instance, they could have the right to abstain, meaning that the models could get back to the user when they are not confident enough about their prediction. This should reduce the risk of inappropriate decisions from a CDT and allow human-machine co-piloting of a food supply chain.

The task of learning to classify data with the possibility to abstain is called Selective Classification. This set of techniques has been around for quite some time now and recently gain new momentum (Chow, 1970; Hendrickx et al., 2021). The general idea is quite simple: the model abstains from the decision when the probability of taking the wrong decision is too high and

> [escaletes] the decision to a human agent who could possibly take into account additional (qualitative) information (Ruggieri et al., 2023).

Applying a Selective Classification implies an obvious trade-off between accuracy and the percentage of abstentions which, in the DSS4LCO initiative, translates into the amount of decisional independence of the CDT framework. The authors believe that implementing this kind of safeguards would be a valuable to make the CDT architecture as trustworthy as possible.

Second, modern machine learning systems are extremely data hungry. Hence, their training (or re-training in the case of stream-based scenarios) is an extremely expensive task. To lower this expense and ease the burden of data (re-)labelling as much as possible, the CDT architecture should suggest proactively to the user the data to review. This can be done through a technique called Active Learning (AL).

AL is a human-in-the-loop machine learning framework that

> attempts to maximize a model's performance gain while annotating the fewest samples possible (Ren et al., 2022).

In an AL framework, the practitioner has at disposal In an AL framework, the practitioner has at disposal many unlabeled data points and a small pool of annotated data. The model is trained on the annotated data, then the unlabeled data is queried according to some criteria (e.g., how informative the samples are for the model). The retrieved samples are labelled by a user, the labelled pool is enlarged, and the training continues through an increasing amount of data until the model reaches good performances or other stopping criteria are met. Other authors (Chabanet et al., 2022; Gardner et al., 2020) recently recognized AL as a useful tool for the creation of CDT frameworks.

5. Conclusions

From the literature review discussed in sections 2.2, 2.3, and 2.4 several research initiatives are investigating the potentials and the benefit of transferring CPPSs technologies and methods, such as DT frameworks, in food supply chains to overcome fundamental challenges, such as: quality assurance, waste reduction, safety, and security management. However, a holistic combination of all the topics for applications of CDT frameworks is missing and the literature is lacking applied case studies to: (i) extend the applications towards whole food supply chains, (ii) implement comprehensive metric indexes, and (iii) develop symbiotic cognitive capabilities towards a real-time autonomous decision-making system without human assistance or limiting human intervention.

This conceptual paper presents the early outcomes of DSS4LCO initiative which aims at implementing a CDT architecture in food supply chains, to investigate potentials of multi-objective optimization methods, under external uncertainties or disruptive events, towards the implementation of an autonomous decision-making system. The paper defines a CDT architecture for food supply chains which distributes the CPPS components among two different domains: a DT domain and a CDT domain. Finally, it introduces some insights of the CDT domain, discussing the challenges to be faced.

Future developments of the DSS4LCO initiative will face a prototype implementation of the defined architecture, relying on a real use-case with the contribution of local stakeholders. This prototype, as a proof-of-concept demonstrator to be validated with experts and local stakeholders, will focus on: (i) the implementation of a virtual model relying on VSM model and the definition of LARG metrics at DT domain level, (ii) the definition of a comprehensive top-level ontology and (iii) the implementation of machine-learning aided decision-making system at CDT domain level. Other components of the defined architecture will be implemented according to available solutions and methods from the exiting literature (such as data exchange with IIoT devices and external databases and the multi-objective optimization engine).

Since the initiative has only accomplished the early first steps of the planned research activities, a lot has to be done to implement the defined architecture, to validate and generalize it. However, these early outcomes must be intended as a first explorative step to provide a reference for future developments, not only of the DSS4LCO initiative, but also of other research initiatives aiming at investigating applications of CDT frameworks in food supply chains.

Funding

The DSS4LCO initiative is supported by the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3 - Call for tender No. 341 of 15 March 2022 of the Italian Ministry of University and Research funded by the European Union – Next Generation EU; Project code PE00000003, Concession Decree No. 1550 of 11 October 2022 adopted by the Italian Ministry of University and Research, CUP I33C22006890001, Project title "ON Foods - Research and innovation network on food and nutrition Sustainability, Safety and Security - Working ON Foods".

Acknowledgements

The authors would like to thank Dr. Anton Dignös from Free University of Bozen-Bolzano for his insightful and constructive comments.

References

Ali, J. A. H., Gaffinet, B., Panetto, H., & Naudet, Y. (2024). Cognitive systems and interoperability in the enterprise: A systematic literature review. Annual Reviews in Control, 57, 100954. https://doi.org/10.1016/j.arcontrol.2024.100954

Azevedo, S. G., Carvalho, H., & Cruz-Machado, V. (2011). A proposal of LARG Supply Chain Management Practices and a Performance Measurement System. International Journal of E-Education, e-Business, e-Management and e-Learning, 7–14. https://doi.org/10.7763/IJEEEE.2011.V1.2

Bagheri, B., Yang, S., Kao, H.-A., & Lee, J. (2015). Cyber-physical Systems Architecture for Self-Aware Machines in Industry 4.0 Environment. IFAC-PapersOnLine, 48(3), 1622–1627. https://doi.org/10.1016/j.ifacol.2015.06.318

Bonney, M. S., de Angelis, M., Dal Borgo, M., Andrade, L., Beregi, S., Jamia, N., & Wagg, D. J. (2022). Development of a digital twin operational platform using Python Flask. Data-Centric Engineering, 3, e1. https://doi.org/10.1017/dce.2022.1

Bottani, E., Bigliardi, B., & Rinaldi, M. (2022). Development and proposal of a LARG (lean, agile, resilient, green) performance measurement system for a food supply chain. IFAC-PapersOnLine, 55(10), 2437–2444. https://doi.org/10.1016/J.IFACOL.2022.10.074

Branke, J., Deb, K., Miettinen, K., & Słowiński, R. (2008). Multiobjective Optimization (J. Branke, K. Deb, K. Miettinen, & R. Słowiński, Eds.; Vol. 5252). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-88908-3

Büchele, F., Hivare, K., Khera, K., Thewes, F. R., Argenta, L. C., Hoffmann, T. G., Mahajan, P. V., Prange, R. K., Pareek, S., & Neuwald, D. A. (2024). Novel Energy-Saving Strategies in Apple Storage: A Review. Sustainability, 16(3), 1052. https://doi.org/10.3390/su16031052

Carvalho, H., Azevedo, S. G., Duarte, S., & Cruz-Machado, V. (2011). Green and Lean Paradigms Influence on Sustainable Business Development of Manufacturing Supply Chains. International Journal of Green Computing, 2(2), 45–62. https://doi.org/10.4018/jgc.2011070103

Casino, F., Kanakaris, V., Dasaklis, T. K., Moschuris, S., Stachtiaris, S., Pagoni, M., & Rachaniotis, N. P. (2021). Blockchain-based food supply chain traceability: a case study in the dairy sector. International Journal of Production Research, 59(19), 5758–5770. https://doi.org/10.1080/00207543.2020.1789238

Chabanet, S., El-Haouzi, H. B., & Thomas, P. (2022). Toward a self-adaptive digital twin based Active learning method: an application to the lumber industry. IFAC-PapersOnLine, 55(2), 378–383. https://doi.org/10.1016/j.ifacol.2022.04.223

Chow, C. (1970). On optimum recognition error and reject tradeoff. IEEE Transactions on Information Theory, 16(1), 41–46. https://doi.org/10.1109/TIT.1970.1054406

Deb, K., Gondkar, A., & Anirudh, S. (2023). Learning to Predict Pareto-Optimal Solutions from Pseudo-weights (pp. 191–204). https://doi.org/10.1007/978-3-031-27250-9_14

Ding, H., Tian, J., Yu, W., Wilson, D. I., Young, B. R., Cui, X., Xin, X., Wang, Z., & Li, W. (2023). The Application of Artificial Intelligence and Big Data in the Food Industry. Foods, 12(24), 4511. https://doi.org/10.3390/foods12244511

Dooley, D. M., Griffiths, E. J., Gosal, G. S., Buttigieg, P. L., Hoehndorf, R., Lange, M. C., Schriml, L. M., Brinkman, F. S. L., & Hsiao, W. W. L. (2018). FoodOn: a harmonized food ontology to increase global food traceability, quality control and data integration. Npj Science of Food, 2(1), 23. https://doi.org/10.1038/s41538-018-0032-6

Douthwaite, J. A., Lesage, B., Gleirscher, M., Calinescu, R., Aitken, J. M., Alexander, R., & Law, J. (2021). A Modular Digital Twinning Framework for Safety Assurance of Collaborative Robotics. Frontiers in Robotics and AI, 8. https://doi.org/10.3389/frobt.2021.758099

Dragoni, M., Bailoni, T., Maimone, R., & Eccher, C. (2018). HeLiS: An Ontology for Supporting Healthy Lifestyles (pp. 53–69). https://doi.org/10.1007/978-3-030-00668-6_4

Erlach, K. (2013). Value Stream Design. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-12569-0

Eyre, J., & Scott, R. (2020). Untangling the requirements of a Digital Twin. https://doi.org/10.13140/RG.2.2.28776.96001

Fernández, F., Sánchez, Á., Vélez, J. F., & Moreno, A. B. (2019). Symbiotic Autonomous Systems with Consciousness Using Digital Twins (pp. 23–32). https://doi.org/10.1007/978-3-030-19651-6_3

Fernández-López, M., Gomez-Perez, A., & Juristo, N. (1997). METHONTOLOGY: from ontological art towards ontological engineering. Engineering Workshop on Ontological Engineering (AAAI97).

Gardner, P., Dal Borgo, M., Ruffini, V., Hughes, A. J., Zhu, Y., & Wagg, D. J. (2020). Towards the Development of an Operational Digital Twin. Vibration, 3(3), 235–265. https://doi.org/10.3390/vibration3030018

Grieves, M. (2014). Digital Twin: Manufacturing Excellence through Virtual Factory Replication. https://www.researchgate.net/publication/275211047

Guidani, B., Ronzoni, M., & Accorsi, R. (2024). Virtual agri-food supply chains: A holistic digital twin for sustainable food ecosystem design, control and transparency. Sustainable Production and Consumption, 46, 161–179. https://doi.org/10.1016/j.spc.2024.01.016

Hamad, F., Liu, I., & Zhang, X. X. (2018, June 10). Food Discovery with Uber Eats: Building a Query Understanding Engine. Uber Blog. https://www.uber.com/en-AT/blog/uber-eats-query-understanding/

Haussmann, S., Seneviratne, O., Chen, Y., Ne'eman, Y., Codella, J., Chen, C.-H., McGuinness, D. L., & Zaki, M. J. (2019). FoodKG: A Semantics-Driven Knowledge Graph for Food Recommendation (pp. 146–162). https://doi.org/10.1007/978-3-030-30796-7_10

Hendrickx, K., Perini, L., Van der Plas, D., Meert, W., & Davis, J. (2021). Machine Learning with a Reject Option: A survey.

Hevner, March, Park, & Ram. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75. https://doi.org/10.2307/25148625

Hoang, L. P., Le, D. D., Tuan, T. A., & Thang, T. N. (2022). Improving Pareto Front Learning via Multi-Sample Hypernetworks.

Hsu, Y., Chiu, J.-M., & Liu, J. S. (2019). Digital Twins for Industry 4.0 and Beyond. 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 526–530. https://doi.org/10.1109/IEEM44572.2019.8978614

Hu, G., & You, F. (2024). AI-enabled cyber-physical-biological systems for smart energy management and sustainable food production in a plant factory. Applied Energy, 356, 122334. https://doi.org/10.1016/j.apenergy.2023.122334

Huang, Y., Ghadge, A., & Yates, N. (2024). Implementation of digital twins in the food supply chain: a review and conceptual framework. International Journal of Production Research, 1–27. https://doi.org/10.1080/00207543.2024.2305804

Jopp, K. (2013). Industry 4.0: The merging of real and virtual worlds. Internet of things drives the fourth industrial revolution | Industrie 4.0: Das zusammenwachsen von realer und virtueller welt: Internet der Dinge treibt die vierte industrielle Revolution an. Stahl Und Eisen, 133(6), 86–88.

Khanzadi, F., Radfar, R., & Pilevari, N. (2024). A review of lean, agile, resilient, and green (LARG) supply chain management in engineering, business and management areas. Decision Science Letters, 13(2), 287–306. https://doi.org/10.5267/j.dsl.2024.3.002

La Scalia, G., Settanni, L., Micale, R., & Enea, M. (2016). Predictive shelf life model based on RF technology for improving the management of food supply chain: A case study. International Journal of RF Technologies, 7(1), 31–42. https://doi.org/10.3233/RFT-150073

Lei, Z., Ul Haq, A., Zeb, A., Suzauddola, M., & Zhang, D. (2021). Is the suggested food your desired?: Multi-modal recipe recommendation with demand-based knowledge graph. Expert Systems with Applications, 186, 115708. https://doi.org/10.1016/j.eswa.2021.115708

Li, Y., Feng, Y., Wang, C., Xing, Z., Ren, D., & Fu, L. (2024). Performance evaluation and optimization of the cascade refrigeration system based on the digital twin model. Applied Thermal Engineering, 248, 123160. https://doi.org/10.1016/j.applthermaleng.2024.123160

Min, W., Liu, C., Xu, L., & Jiang, S. (2022). Applications of knowledge graphs for food science and industry. Patterns, 3(5), 100484. https://doi.org/10.1016/j.patter.2022.100484

Mousavi, S. M., Sadeghi R., K., & Lee, L. S. (2023). An interactive analytics approach for sustainable and resilient case studies: a machine learning perspective. Journal of Business Analytics, 6(4), 276–293. https://doi.org/10.1080/2573234X.2023.2202691

Nabavi, S. R., Jafari, M. J., & Wang, Z. (2023). Deep Learning Aided Multi-Objective Optimization and Multi-Criteria Decision Making in Thermal Cracking Process for Olefines Production. Journal of the Taiwan Institute of Chemical Engineers, 152, 105179. https://doi.org/10.1016/j.jtice.2023.105179

Piardi, L., Leitao, P., & de Oliveira, A. S. (2020). Fault-Tolerance in Cyber-Physical Systems: Literature Review and Challenges. 2020 IEEE 18th International Conference on Industrial Informatics (INDIN), 29–34. https://doi.org/10.1109/INDIN45582.2020.9442209

Pizzuti, T., Mirabelli, G., Grasso, G., & Paldino, G. (2017). MESCO (MEat Supply Chain Ontology): An ontology for supporting traceability in the meat supply chain. Food Control, 72, 123–133. https://doi.org/10.1016/j.foodcont.2016.07.038

Pizzuti, T., Mirabelli, G., Sanz-Bobi, M. A., & Goméz-Gonzaléz, F. (2014). Food Track & Trace ontology for helping the food traceability control. Journal of Food Engineering, 120, 17–30. https://doi.org/10.1016/j.jfoodeng.2013.07.017

Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. Computers and Electronics in Agriculture, 184, 105942. https://doi.org/10.1016/j.compag.2020.105942

Ren, P., Xiao, Y., Chang, X., Huang, P.-Y., Li, Z., Gupta, B. B., Chen, X., & Wang, X. (2022). A Survey of Deep Active Learning. ACM Computing Surveys, 54(9), 1–40. https://doi.org/10.1145/3472291

Rother, M., & Shook, J. (2003). Learning to see: value stream mapping to add value and eliminate muda. Lean enterprise institute.

Ruggieri, S., Alvarez, J. M., Pugnana, A., State, L., & Turini, F. (2023). Can We Trust Fair-AI? Proceedings of the AAAI Conference on Artificial Intelligence, 37(13), 15421–15430. https://doi.org/10.1609/aaai.v37i13.26798

Sahu, A. K., Sharma, M., Raut, R. D., Sahu, A. K., Sahu, N. K., Antony, J., & Tortorella, G. L. (2023). Decision-making framework for supplier selection using an integrated MCDM approach in a lean-agile-resilient-green environment: evidence from Indian automotive sector. The TQM Journal, 35(4), 964–1006. https://doi.org/10.1108/TQM-12-2021-0372

Schweichhart, K. (2016). Reference Architectural Model Industrie 4.0 (RAMI4.0) - An Introduction. Plattform Industrie 4.0. https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/rami40-an-introduction.html

Schweizer, W. (2013). Wertstrom Engineering: Typen- und variantenreiche Produktion. epubli GmbH.

Sharma, R., & Gupta, H. (2024). Leveraging cognitive digital twins in industry 5.0 for achieving sustainable development goal 9: An exploration of inclusive and sustainable industrialization strategies. Journal of Cleaner Production, 448, 141364. https://doi.org/10.1016/j.jclepro.2024.141364

Singh, G., Rajesh, R., Daultani, Y., & Misra, S. C. (2023). Resilience and sustainability enhancements in food supply chains using Digital Twin technology: A grey causal modelling (GCM) approach. Computers & Industrial Engineering, 179, 109172. https://doi.org/10.1016/j.cie.2023.109172

Tan, J. K. N., Law, A. W.-K., Kumar Maan, A., & Cheung, S. H. (2023). Digital-twin-controlled ventilation for real-time resilience against transmission of airborne infectious disease in an indoor food court. Building Services Engineering Research and Technology, 44(6), 641–658. https://doi.org/10.1177/01436244231204450

Tekaat, J. L., Anacker, H., & Dumitrescu, R. (2021). The Paradigm of Design Thinking and Systems Engineering in the Design of Cyber-Physical Systems: A Systematic Literature Review. 2021 IEEE International Symposium on Systems Engineering (ISSE), 1–8. https://doi.org/10.1109/ISSE51541.2021.9582548

Valero, M. R., Hicks, B. J., & Nassehi, A. (2023). A Conceptual Framework of a Digital-Twin for a Circular Meat Supply Chain (pp. 188–196). https://doi.org/10.1007/978-3-031-18326-3_19

Wang, Z., Li, J., Rangaiah, G. P., & Wu, Z. (2022). Machine learning aided multi-objective optimization and multi-criteria decision making: Framework and two applications in chemical engineering. Computers & Chemical Engineering, 165, 107945. https://doi.org/10.1016/j.compchemeng.2022.107945

West, T. D., & Blackburn, M. (2017). Is Digital Thread/Digital Twin Affordable? A Systemic Assessment of the Cost of DoD's Latest Manhattan Project. Procedia Computer Science, 114, 47–56. https://doi.org/10.1016/j.procs.2017.09.003

Yadav, V. S., Singh, A. R., Gunasekaran, A., Raut, R. D., & Narkhede, B. E. (2022). A systematic literature review of the agro-food supply chain: Challenges, network design, and performance measurement perspectives. Sustainable Production and Consumption, 29, 685–704. https://doi.org/10.1016/j.spc.2021.11.019

Zheng, X., Lu, J., & Kiritsis, D. (2022). The emergence of cognitive digital twin: vision, challenges and opportunities. International Journal of Production Research, 60(24), 7610–7632. https://doi.org/10.1080/00207543.2021.2014591

Zulaika, U., Gutiérrez, A., & López-de-Ipiña, D. (2018). Enhancing Profile and Context Aware Relevant Food Search through Knowledge Graphs. UCAmI 2018, 1228. https://doi.org/10.3390/proceedings2191228