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Conceptual and formal models for design, adaptation, and control of digital twins in supply chain ecosystems

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ABSTRACT

The design and adaptation of digital twins in supply chains are of high relevance for academia and industry alike. While numerous prototype-based use cases have been reported, the literature lacks studies revealing generalizable methodological principles. This paper elaborates on conceptual and formal models of digital twins in the supply chain. First, we define a new notion named digital supply chain ecosystem extending the recently developed intelligent digital twin framework. A digital ecosystem is a set of digital technologies, AI-based knowledge management systems, cloud spaces, and platforms that encapsulate supply chain data enabling digital twins and simulation models. Second, we elaborate on a digital twin as a complex phenomenon comprising systems, technological-organizational models, and management decision-making support perspectives. We offer a dynamic, quantitative framework for digital twins as a decision-making support and modeling environment using control theory. Third, we introduce two views of building and adapting digital twins, i.e., object-driven and data-driven approaches. Their principle schemes are defined and discussed. Finally, we outline a generalized framework of the cyber-physical supply chain comprised of a digital ecosystem, digital twin, human-AI collaboration space, and the physical supply chain. Application scenarios are considered, e.g., using digital twins for stress testing of supply chain resilience in the setting of tariff-driven shocks as well as building resilient and viable agricultural ecosystems.

1. Introduction

A digital twin of the supply chain is “a virtual system comprised of (i) a digital visualization of a physical supply chain and its elements (e.g., firms, flows, products) in a computer model, (ii) digital technologies providing data about the physical object (e.g. sensors, blockchain, clouds), and (iii) descriptive, predictive, and prescriptive analytics for decision-making support” [1].

The design and adaptation of digital twins in supply chains are of high relevance for academia and industry alike [2–5]. The global supply chain digital twin market size was valued at USD 2.49 billion in 2022 and is expected to grow at a compound annual growth rate (CAGR) of 12.0 % from 2023 to 2030 [6]. Market analyses indicate the global market for digital twins will grow about 30 to 40 percent annually, reaching $125 billion to $150 billion by 2032 [7].The market is anticipated to grow due to the widespread adoption of Internet of Things (IoT) devices and sensors throughout the supply chain, which generate vast amounts of data [8,9].

Digital twins leverage data to create accurate process models, deliver insights into real-time operations, and enable predictive analytics for more informed decision-making [10,11]. Furthermore, integrating advanced analytics and artificial intelligence (AI) into supply chain digital twins enhances their functionality and effectiveness [12–14]. For example, in a retail supply chain, digital twins can help improve on-time delivery by up to 20 percent, lead to a 10 percent reduction in labor costs, and increase revenue by 5 percent [7].

However, while the benefits of digital twins in the supply chain seem to be well perceived and understood, the problem of designing and adapting digital twins remains underexplored [15–18]. Existing software such as advanced planning and scheduling (APS), warehouse management systems (WMS), and transportation management systems (TMS) have automated large parts of the supply chain in the past decade, streamlining the integration of suppliers, buyers, and shippers. However, system integrations have not always automatically translated into digital twins. Despite the visible progress and the growing importance of digital twins in the supply chain, the literature lacks studies revealing

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generalizable methodological principles for their deployment and adjustment [19–21].

Our study aims to close this research gap. Our objective is to propose conceptual and formal models of digital twin design and adaptation in the supply chain. Our contributions are as follows. First, we define a new notion named digital supply chain ecosystem extending the recently developed intelligent digital twin (iDT) framework [12]. Second, we elaborate on a digital twin as a complex phenomenon comprising systems, technological-organizational, modeling, and management decision-making support perspectives. We offer a dynamic, quantitative framework for decision-making support and modeling in digital twins using control theory. Third, we introduce two views of building digital twins, i.e., object-driven and data-driven approaches. Their principle schemes are defined and discussed. Finally, we outline a generalized framework of the cyber-physical supply chain comprised of a digital ecosystem, digital twin, human-AI collaboration space, and the physical supply chain. Two application scenarios are considered.

The remainder of this paper is organized as follows. In Section 2, we discuss different levels of digital twins and introduce a digital ecosystem notion. Section 3 is devoted to conceptual and formal models of decision-making support in digital twins. In Section 4, we elaborate on object-driven and data-driven approaches to building and adapting digital twins. Section 5 offers a generalized framework of the cyber-physical supply chain and discusses two distinct application scenarios. Section 6 concludes this paper with a discussion and summary of main insights.

2. From digital replicas to intelligent digital twins and ecosystems

In this section, we first describe the developments of digital twins in supply chains from simple digital replicas toward human-AI collaboration. Then, a new notion of digital ecosystems is defined in relation to digital twins.

2.1. From digital replicas to intelligent digital twins

Definitions of supply chain digital twins in the literature emphasize their diverse visions and technological foundations. Van der Valk et al. [22] refer to "a solution for better visualization and understanding of supply chains and an opportunity for further analysis, simulation, and optimization." Tozanli and Saenz [8] highlight "a combination of multiple enabling technologies, such as sensors, cloud computing, AI, advanced analytics, simulation, visualization, and augmented and virtual reality." Ivanov and Dolgui [23] define digital twins as "computerized models that represent the network state for any given moment in time." Additional characteristics of digital twins drawn from studies by Singh et al. [24], Badakhsan and Ball [2], Sharma et al. [25], Nguyen et al. [26], Ivanov [1], and Li et al. [27] emphasize their adaptability, human-AI interface, model-based decision-making support, and technological-organizational perspective.

Digital twins can improve visibility, transparency, collaboration, and traceability [14,28,29]. Their applications range from basic process monitoring, such as tracking the location of shipping containers, to more advanced functions, like developing new management principles grounded in end-to-end visibility and digital collaboration [20,30,31]. These advancements are particularly valuable for managing complex, multi-echelon, omnichannel supply chains, where visibility is often limited, and companies may lack awareness of upstream suppliers or last-mile logistics structures. In such scenarios, digital twins provide critical insights by analyzing the structure of physical supply chain networks through cloud-based data [32–34].

Ivanov [12] identified three levels of digital twins based on the degree of human-AI collaboration (Fig. 1).

A traditional digital twin replicates key components of the network, such as its structure, products, customers, and associated processes, i.e., production, distribution, and sourcing, and their control [35–37]. Supported by descriptive, predictive, and prescriptive analytics, digital twins are augmented with dashboards that visualize performance in real time [23,38].

Supplemented by AI, cognitive digital twins, i.e., the digital twin of the *second level* are extended with self-learning, reasoning, and decision-making capabilities using real-time data [11,39]. While traditional digital twins replicate physical objects based on human knowledge, cognitive twins are designed for self-learning and reasoning abilities. They are able to adjust decision-making rules based on real-time data and previous experiences of managers, e.g., in handling disruptions that have already hit the supply chain in the past [12,40].

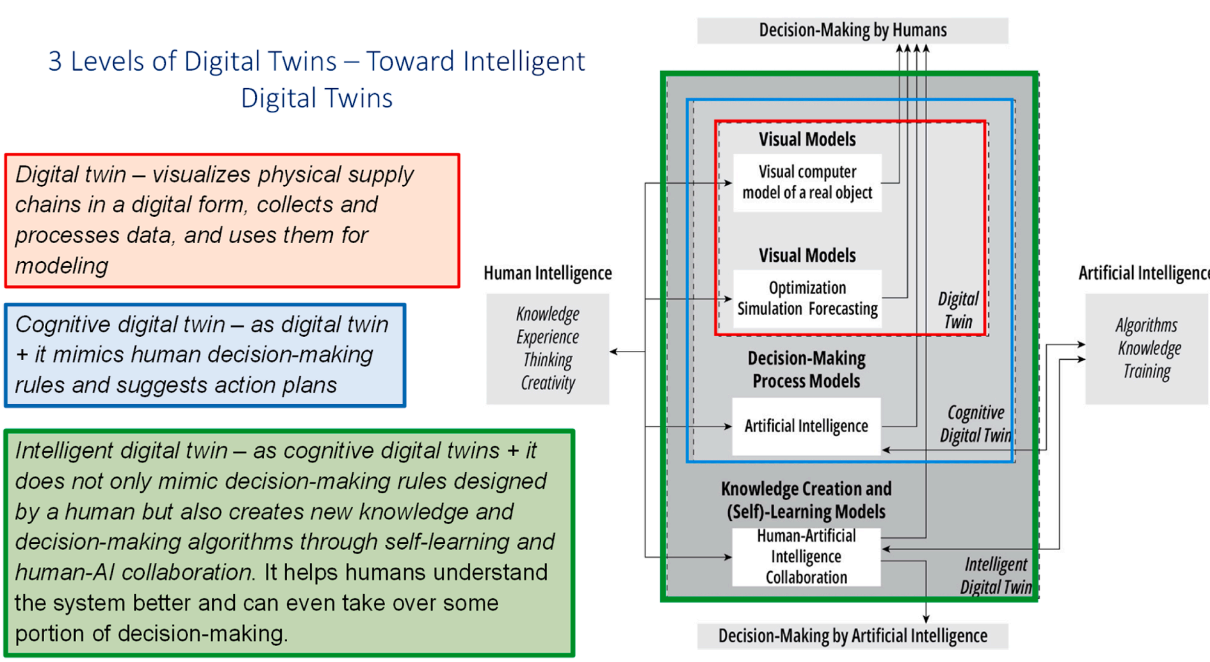

Fig. 1. Three levels of digital twins (based on [12]).

While cognitive digital twins can suggest AI-based recommendations based on previous knowledge and facing known patterns, intelligent digital twins (iDT) - which we refer to as digital twin of the *third level* help uncover new knowledge about the real object, fostering a self-learning and knowledge-creating cognitive environment within a human–machine decision-making loop toward reconfigurable supply chain [41]. iDTs enable humans and AI to collaborate, learn from each other, and delegate decision-making tasks [42–45]. This idea is linked to AI agents, which are automated decision-makers. Consider a global retail chain where planners might focus detailed analysis on top-selling products in major markets, applying generic forecasting rules to "normal" products. AI agents could analyze all products with the same depth and could simultaneously “process store-level historical sales for each size-color combination, local weather forecasts and seasonal patterns, pricing and promotion data from neighboring competitors, social media sentiment by region, and local events and school calendars that might impact shopping patterns” [46]. When demand patterns shift, agents could trace these implications across the supply chain.

Human–AI collaboration in iDTs is driven by several factors and can be divided into three main areas as depicted in Fig. 2.

First, while humans can solve complex problems, they often struggle to precisely define their decision-making rules, making it challenging for machines to replicate them. In these cases, AI algorithms typically excel in standardized tasks, but humans bring experience, creativity, and adaptability, complementing AI’s capabilities in non-standardized situations. Second, human’s ability to delegate tasks to AI. AI algorithms, through training, can not only improve their performance but also help enhance human metaknowledge. iDTs can assist humans in identifying multi-echelon supply chain network structures, buyer–supplier relationships, and demand patterns through improved visibility and AI-enabled collaboration. This leads to better understanding and more accurate decision-making regarding demand, supply, and process management.

In the iDT, generative AI technologies play a crucial role [43,47]. Generative AI continues to evolve, and understanding their interaction with digital twins is crucial [48,49]. Elaborating on this relationship could enhance the clarity of how digital twins can leverage generative AI for enhanced predictive analytics, product design, and optimization of supply chain processes [42,50]. For instance, specific use cases, such as automated design generation based on real-time data, could illustrate the transformative potential of this synergy [51,52].

When considering digital twins with AI agents, AI hallucination should be addressed, i.e., responses generated by AI may contain false or misleading information presented as facts and used for decision recommendations [53]. Organizations must ensure AI outputs are grounded in real-time and data are verified from reliable sources. This involves integrating clean, validated input from systems like ERP, IoT, and smart sensors, using human-in-the-loop oversight, and employing explainable AI to make decision logic transparent. Hybrid models that combine deterministic simulations with machine learning can reduce reliance on generative AI, while continuous feedback loops and detailed audit trails help identify and correct false outputs. Fine-tuning models on domain-specific data further minimizes the risk of hallucination and improves operational reliability.

2.2. Digital ecosystems

Literature on digital twins typically presumes a two-layer system composition: physical and digital [4,9]. With the digital ecosystem, we extend this traditional view toward a three-level structure. We define the digital ecosystem as follows:

A digital ecosystem is a set of digital technologies, AI-based knowledge management systems, cloud spaces, and platforms that encapsulate supply chain data enabling digital twins and simulation models.

Using digital ecosystems, dynamic, data-driven digital twins can be built. The role of a digital ecosystem in cyber-physical supply chain framework is visualized in Fig. 3.

For an understanding of ecosystem notion and its role in the digital intertwining of supply chains, we start with a discussion about the integration of data-driven and model-based decision-making support (Fig. 4 and Fig. 5).

Information for decision-making support is encapsulated from four different sources: object (i.e., the physical supply chain *data*), subject (i.e., human *knowledge*), environment (i.e., *learning* about uncertainty), and modeling (i.e., *simulation* results). As shown in Fig. 5, digital twin should accumulate all four sources.

The principle schema of integrated data-driven and model-based decision-making support in digital twins is composed of the following elements:

- A physical *object* (i.e., the supply chain) characterized by:
  - x(t): a state vector that encapsulates information about the supply chain dynamics at each time point (e.g., production volume);

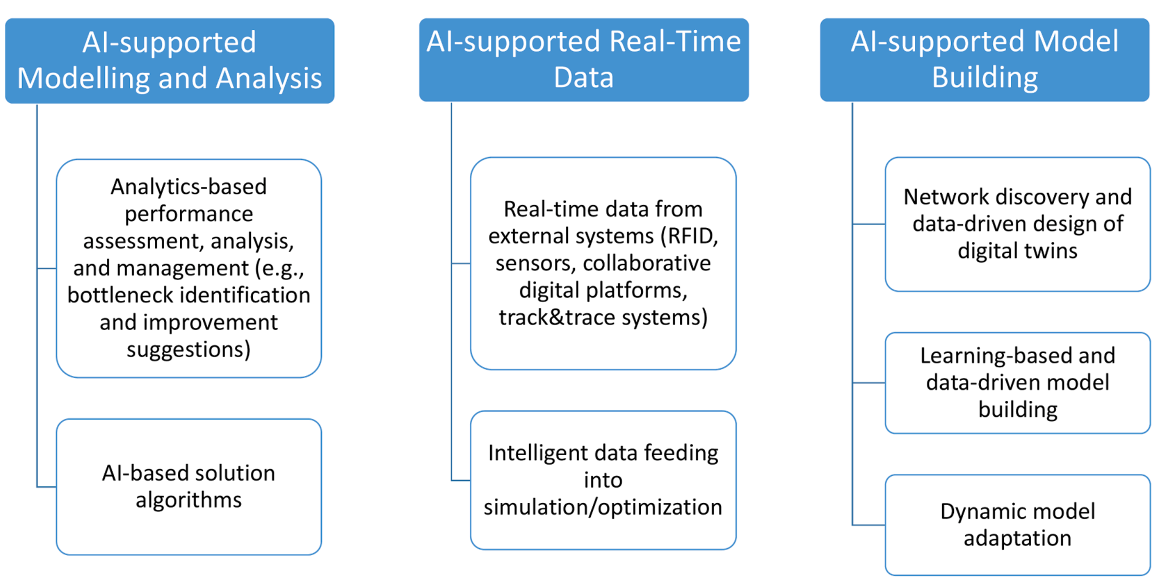

Fig. 2. Integration of simulation and AI.

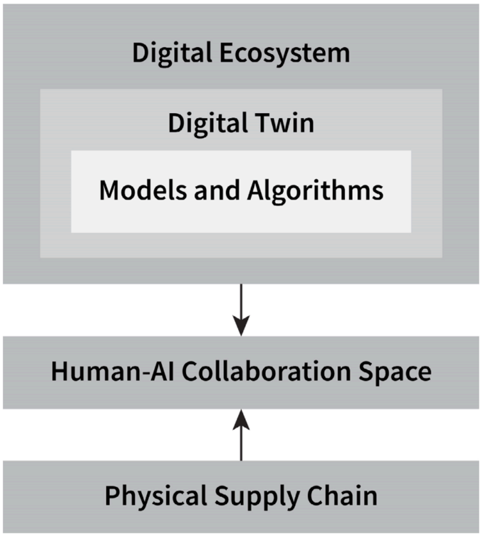

Fig. 3. Role of a digital ecosystem in cyber-physical supply chain framework.

- ξ(t): a perturbation vector illustrating the dynamics of disruptions, the integrity of which is associated with $\Xi(\mathbf{x}(t), t)$;
- α(t): a vector characterizing supply chain elements (e.g., suppliers) performing with deviations from a plan;
- β(t): a vector characterizing processes (e.g., inventory replenishment) performing with deviations from a plan.

• A *subject* (i.e., a decision-maker) characterized by:
- u(t): a control vector representing a plan for process execution (e.g., production or distribution process);
- y(t): observed performance of supply chain processes;
- $\mathbf{v}(\mathbf{x}(t), t)$: a vector representing correction actions (i.e., the control actions adapting the supply chain processes u(t) in case of disruptions);

• A *model* (i.e., the replication of the physical object behavior $\mathbf{x}(t)$ in a controlled digital environment and testing alternatives for the improvement of performance $\mathbf{y}(t)$ through optimization of $\mathbf{u}(t)$ and $\mathbf{v}(t)$ in the presence of $\boldsymbol{\xi}(t)$

• A digital *object* (i.e., the digital supply chain ecosystem with a regularly updated, sensed footprint of a real object encapsulating data, information, and knowledge about a physical object and its dynamics $\mathbf{x}(t)$).

Our understanding of a physical supply chain is, in essence, a combination of data and knowledge about material, information, and financial flows. In other words, a *subject* (i.e., a decision-maker) observes the *object* (i.e., the supply chain) through data and information. That is why we formalize the digital twin through the lens of control theory. Control theory has a unique mathematical apparatus allowing to connect information and material flows through integration of state and control variables based on feedback mechanisms [54–56]. We acknowledge that control theory is one possible method for modeling digital twins. Other approaches, such as game theory, are needed to model collaboration and behavioral elements of digital twins.

Based on data and information combined with expert knowledge, supply chain *models* are developed. Their objective is to represent the physical supply chain, its process dynamics, and decision-making rules. Models help forecast, optimize, and simulate supply chain operations dynamics and performance impacts, e.g., for different market development scenarios, disruptions, and changes in production-ordering control policies. We note that the analytics part can also include algorithms, i.e., "model free" methods such as machine and deep learning [10,45,57,58]. However, our data and knowledge about the supply chain are hardly complete, so the models will be. That is why *environment* is a category that should be considered in order to increase the model's completeness, accuracy, and validity. Environment represents a space of uncertainty, which can be known (e.g., through some probability distribution functions), partially known, or unknown. In the course of object evolution, the subject learns more about the object and its environment, reducing uncertainty and improving model quality.

The interactions between the four elements in the proposed principle schema of integrated data-driven and model-based decision-making support in digital twins are driven by sensing, replicating, modeling, and control. Ecosystems are comprised of a set of digital technologies (e.g., Internet-of-Things, Industry 4.0, Blockchain), AI-based knowledge management systems, and data spaces and platforms (e.g., collaborative supplier portals) [30]. They are sensing data from the physical supply chain. Building of models and digital twins to enable decision-making

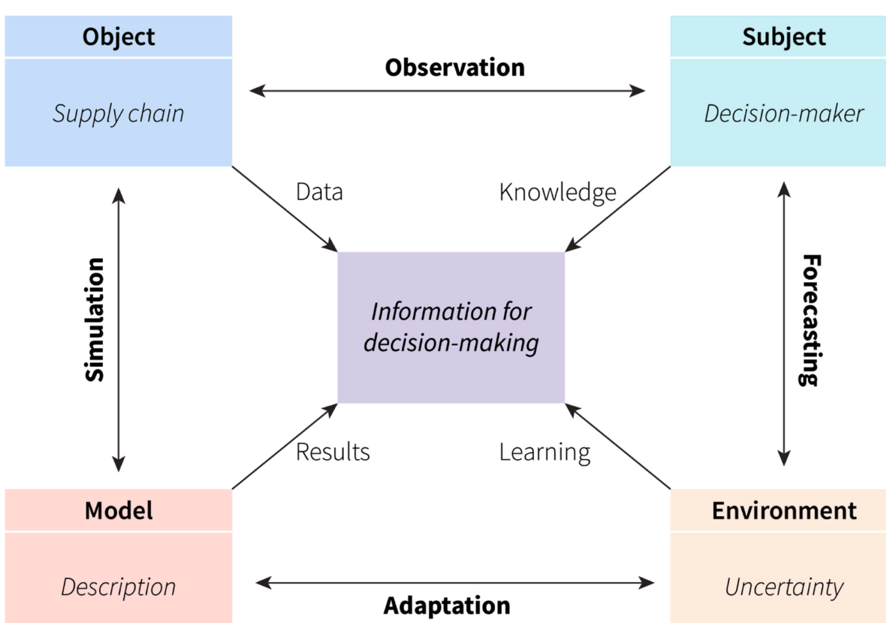

Fig. 4. Sources of information for decision-making support.

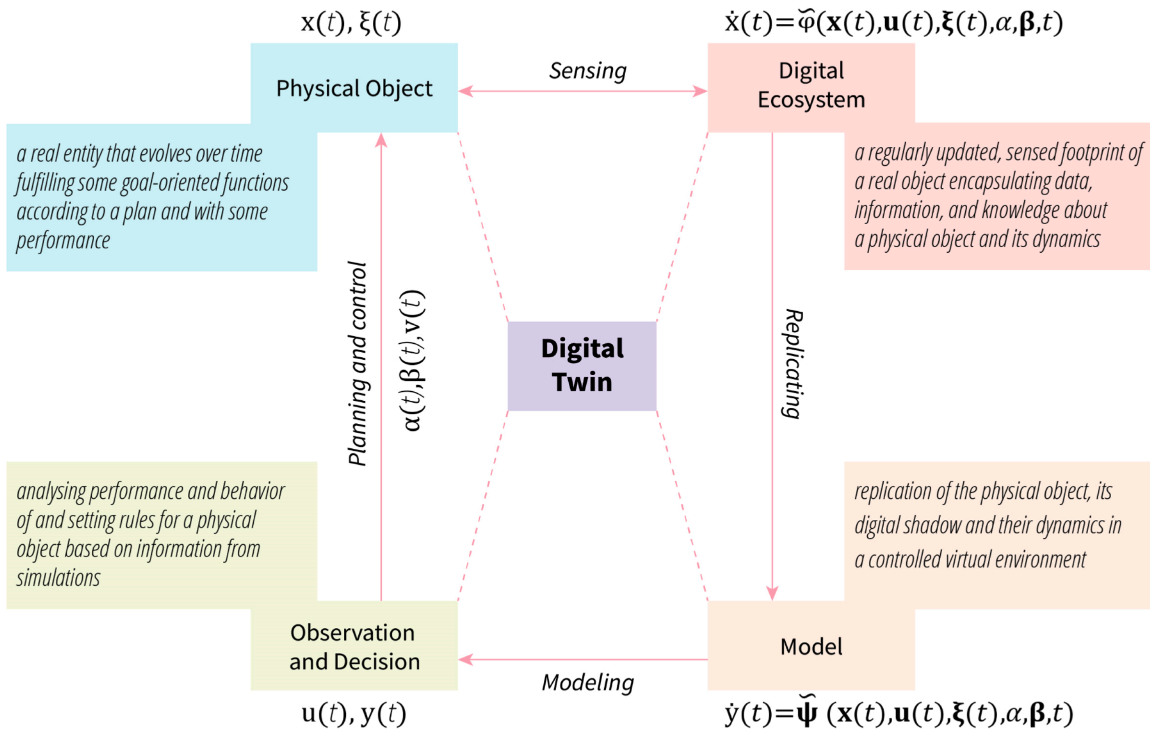

Fig. 5. Principle schema of integrated data-driven and model-based decision-making support in digital twins.

support for planning and control is based on physical object and ecosystem observability (Fig. 6).

Object-driven design and adaptation of digital twins is typical for technical systems, e.g., aviation and civil engineering sectors, where building a prototype can be costly and trigger significant safety risks. In this case, digital twins are virtual replicas of a physical object, system, or process used to simulate potential real-life scenarios and behaviors and deliver analytical insights and visualizations. This approach presumes full visibility and knowledge about the physical object. Moreover, a digital model exists without direct interactions with the physical object. In the case of end-to-end supply chain visibility (i.e., its full observability), digital twins can be built to replicate the physical object, its structure, processes, and coordination rules. However, end-to-end visibility is a challenging problem in supply chain management practice [19,27].Very frequently, supply chains are only partially or even marginally observable. In this case, a data-driven approach to building digital twins can be considered based on the recognition of the physical object from data, and so creating the digital twin from an ecosystem. In this approach, a digital twin exists together with the physical system, adapts to physical changes, and allows a better understanding of the physical system. Moreover, paired with AI and generative AI, digital twins can help predict future scenarios and suggest decisions, ultimately leading to self-monitoring, self-control, and self-adaptation of supply chains. We will discuss these two approaches more detailed in Section 4.

3. Generalized models of digital twinning in the supply chain

In this section, we delve into presenting conceptual and formal models of digital twinning in the supply chain. Digital twin is a complex phenomenon comprising system, technological-organizational, modeling, and management decision-making support perspectives. Each of them deserves a separate analysis, and they are interlinked with each other (Fig. 7).

The system and modeling views (the upper left corner and lower right corner, respectively) have been analysed in Section 2. The technology-organizational view (the lower left corner) reflects technological composition and organizational implementation of digital twins [1,19]. Digital twins integrate – mainly in a decentralized way - the

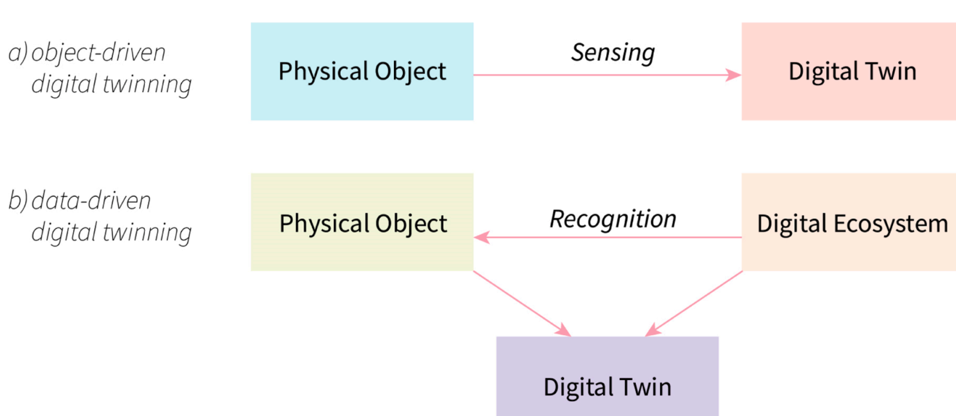

Fig. 6. Physical object and ecosystem observability for design and adaptation of digital twins.

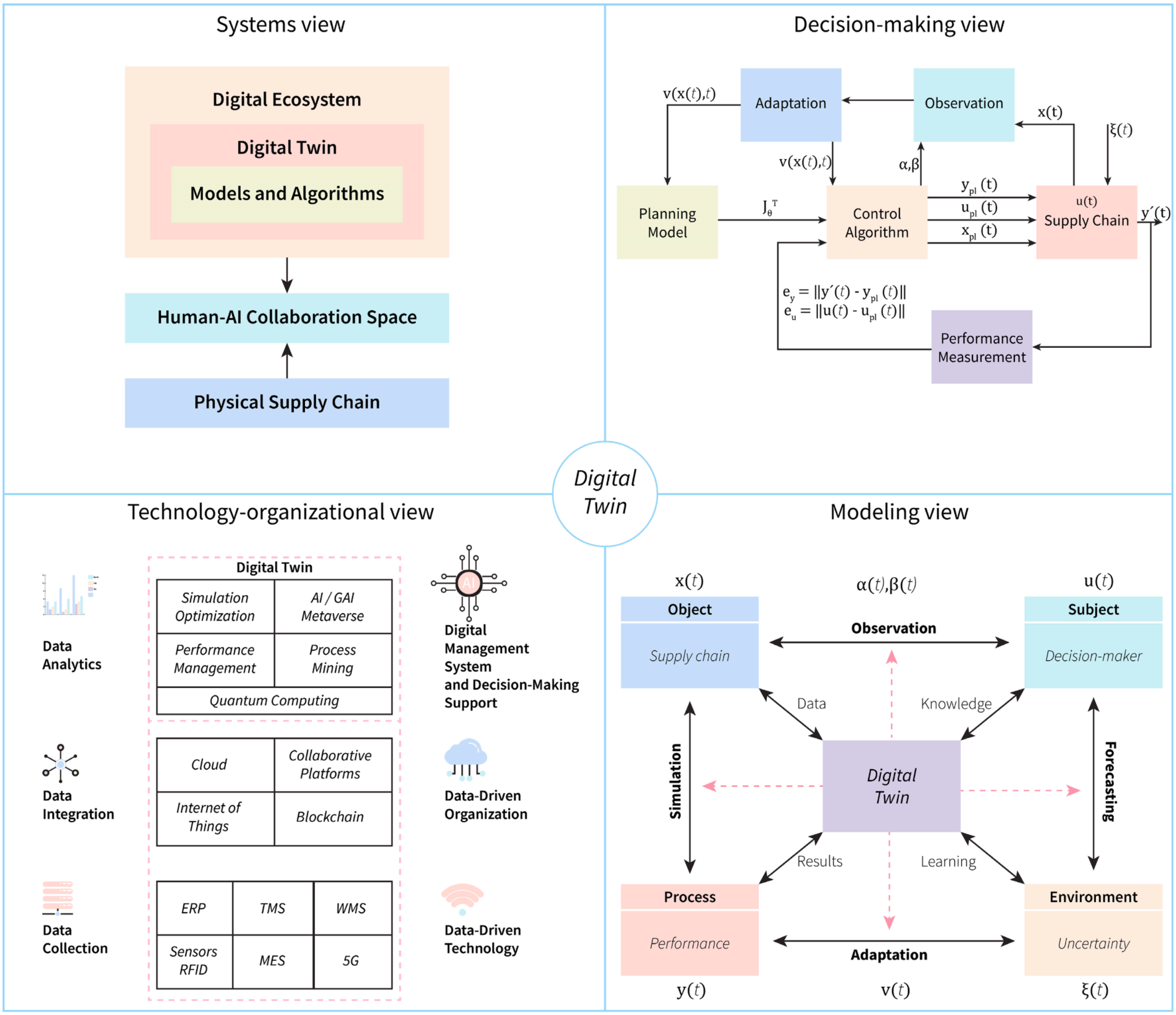

Fig. 7. Perspectives of digital twins in the supply chain.

existing supply chain management information systems, including ERP, TMS, WMS, and MES, as well as IoT technologies such as sensors and 5G/6 G in cloud platforms, Blockchain, and collaborative portals (e.g., SupplyOn, see [30]). Such an integration frames a digital supply chain ecosystem supplemented by predictive, prescriptive, and descriptive analytics, process mining, and AI/GenAI/Metaverse technologies. The resulting digital management system allows for both data-driven, model-based decision—making support and AI-based adjustment of models and algorithms. Through information feedback from physical systems, digital twins can help adjust policies and constraints of planning models. For example, a manufacturing company can use a digital twin to optimize policies for outbound logistics [7]. In another example that we observed in industry, sensors at an assembly line have informed about real movements of workers, and this information was used by a digital twin to adjust a production planning model automatically.

One of the key advantages of digital supply chain twins is the possibility to use data for digital decision-making support across different departments and even in cross-department processes. Consider a potential scenario. Digital twin contains transactional data about customers and suppliers. Sales and supplier spending are therefore visible to managers. For example, a procurement director can analyze how the purchasing budget has been spent and what the most expensive suppliers are. One can also obtain useful information about supplier concentration and their risk exposure. On the sales side, information about revenues and customer concentration can be used for digitally informed sales and operations planning. Interestingly, process mining becomes possible based on the data. For example, data about inventory, production, and order quantities can help identify purchasing processes in the company and the degree of their synchronization with production planning.

We now focus on the decision-making view (the upper right corner). The decision-making view of the digital twin is shown in Fig. 8.

The decision-support system comprises the following elements: planning model, control algorithm, object (i.e., the supply chain), performance measurement, observation, and adaptation. We adopt the following notations consistent with Ivanov [59]:

- JΘT: multi-objective performance vector of a planning model;
- upl(t): a control vector representing a trajectory of a planned process (e.g., production or distribution process);
- $\mathbf{Q}(\mathbf{x}(t), t)$: a vector encompassing all potential realizations (alternatives) of a planned process;
- ypl(t), y’ (t): planned and measured values of performance indicators, respectively;
- ξ(t): a vector illustrating the dynamics of disruptions, the integrity of which is associated with $\Xi(\mathbf{x}(t), t)$;
- x(t): a state vector that characterizes the supply chain at each time point (e.g., production volume);
- e is a deviation between planned and actual performance and processes;

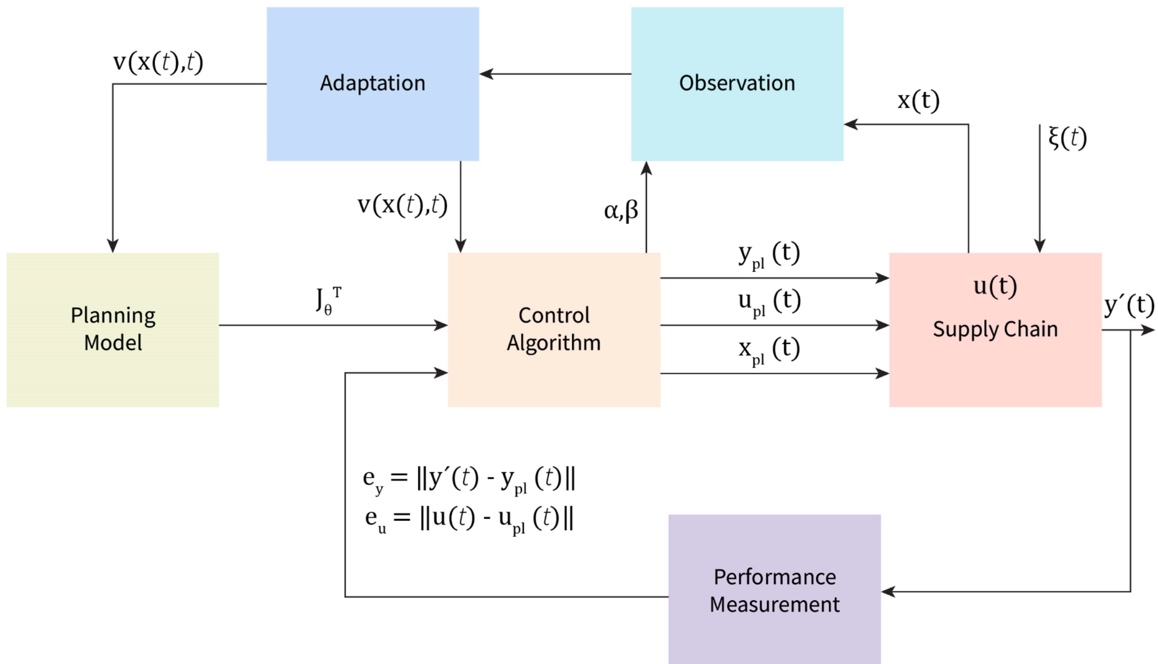

Fig. 8. The decision-making view of the digital twin as a dynamic control system.

- α(t): a vector characterizing structural elements performing with deviations from plan;
- β(t): a vector characterizing process elements performing with deviations from plan;
- $\mathbf{v}(\mathbf{x}(t), t)$: A vector representing correction actions (i.e., the control actions adapting the supply chain processes upl(t));
- $\mathbf{V}(\mathbf{x}(t), t)$: A set of possible regulation control inputs$\mathbf{v}(\mathbf{x}(t), t)$

The control mechanism for the supply chain can be expressed as a dynamic system, delineated by Eq. (1), Eq. (2) and Eq. (3):

$$\dot{\mathbf{x}}(t) = \widetilde{\boldsymbol{\phi}}(\mathbf{x}(t),\, \mathbf{u}(t),\, \boldsymbol{\xi}(t),\, \alpha, \boldsymbol{\beta}, t) \tag{1}$$

$$\dot{\mathbf{y}}(t) = \widetilde{\psi}(\mathbf{x}(t), \mathbf{u}(t), \boldsymbol{\xi}(t), \alpha, \boldsymbol{\beta}, t) \tag{2}$$

$$\mathbf{u}(t) = \| \mathbf{u}_{pl}^{\mathrm{T}}(t), \mathbf{v}^{\mathrm{T}}(\mathbf{x}(t), t)\|^{\mathrm{T}};\ \mathbf{u}_{pl}(t) \in \mathbf{Q}(\mathbf{x}(t), t);\ \ \mathbf{v}(t)(\mathbf{x}(t), t) \in \mathbf{V}(\mathbf{x}(t), t), \tag{3}$$

$$\boldsymbol{\xi}(t) \in \boldsymbol{\Xi}(\mathbf{x}(t), t);\ \ \boldsymbol{\beta} \in B,\ \mathbf{x}(t) \in \mathbf{X}(\boldsymbol{\xi}(t), t),\ \mathbf{x}(T_0) \in \mathbf{X}_0(\boldsymbol{\beta}),\ \ \mathbf{x}(T_f) \in \mathbf{X}_f(\boldsymbol{\beta})$$

where B represents a domain of permissible parameter values (such as inventory levels) and$\mathbf{X}(\boldsymbol{\xi}(t), t)$ signifies a domain of allowable states. Vectors defined in Eqs. (1) and (2) are subject to spatio-temporal constraints, as specified in set (3) at times $t = T_0$ and $t = T_f$.

Fig. 8 delineates a system-cybernetic schema of decision-making support. Based on a planning model, a certain level of performance, denoted as a multi-objective vector $\mathbf{J}_{\boldsymbol{\Theta}}^{\mathrm{T}}$ (e.g., annual revenues, production quantities, on-time delivery, and sales), where subscript $\boldsymbol{\Theta}$ corresponds to a set of models used in the dynamic system. In the present paper, we use only a material flow model. However, other models like financial and information flow control can be included framing a multi-model complex ([60], chapter 10).

A control algorithm determines process plans for achieving the targets $\mathbf{J}_{\boldsymbol{\Theta}}^{\mathrm{T}}$ as control trajectories $\mathbf{u}_{pl}(t)$ (e.g., a production-distribution plan) aiming to transform available resources into the desired output with a specific performance level $\mathbf{y}(t)$ (e.g., monthly production quantities and costs). At each point of time, the supply chain is characterized by a state vector $\mathbf{x}(t)$ and performance vector **y'** (t).

$\mathbf{u}_{pl}(t)$ is subject to real disruptions ξ(t) which impact the supply chain. The state and performance vectors $\mathbf{x}(t)$ and **y'** (t) are continuously monitored and observed. Performance deviations e from planned performance and process execution are recorded. If $e > 0$, $\boldsymbol{\alpha}(t)$ and $\boldsymbol{\beta}(t)$ vectors are formed representing structural and process elements performing with deviations from plan, respectively.

Finally, adaptation$\mathbf{v}(\mathbf{x}(t), t)$s are implemented through either re-planning using the control algorithm and the existing planning model or even through a model adaptation. $\mathbf{u}_{pl}(t)$ and $\mathbf{y}(t)$ are updated. The input data essential for supply chain adaptation are gathered in real-time subject to performance maximization (4):

$$J_G = J_G\big(\mathbf{x}(t), \mathbf{u}_{pl}(t), \mathbf{v}(\mathbf{x}(t), \boldsymbol{\xi}), \boldsymbol{\xi}\big) \rightarrow \underset{\mathbf{u}\in\Delta}{max} \tag{4}$$

We note that J_G is a scalar form of $\mathbf{J}_{\boldsymbol{\Theta}}^{\mathrm{T}}$. A transition procedure from the vector $\mathbf{J}_{\boldsymbol{\Theta}}^{\mathrm{T}}$ to J_G is outside of this paper. We refer to [60] for details of such a transition.

Through adaptation, a transition from the actual supply chain state trajectory$\mathbf{x}(t)$ to the planned (or a new one) $\mathbf{x}_{pl}(t)$ within the time interval $(t', t''] \in (T_0, T_f]$ or by the final time $\mathbf{x}(T_f) = \mathbf{x}_{pl}(T_f)$ as detailed in Eqs. (5) and (6):

$$\Delta\mathbf{x}(t) = \int_{t'}^{t''} \big(\mathbf{x}(\tau) - \mathbf{x}_{pl}(\tau)\big)^{\mathrm{T}} \big(\mathbf{x}(\tau) - \mathbf{x}_{pl}(\tau)\big)\, d\tau \tag{5}$$

$$\Delta\mathbf{x}(T_f) = \big(\mathbf{x}(T_f) - \mathbf{x}_{pl}(T_f)\big)^{\mathrm{T}} \big(\mathbf{x}(T_f) - \mathbf{x}_{pl}(T_f)\big) \tag{6}$$

By broadening the scope of the general case to include$\mathbf{v}(\mathbf{x}(t), t)$ Equations (1) through (3), we can obtain$\mathbf{u}_{pl}(t)$, $\boldsymbol{\nu}(\mathbf{x}(t),\, t)$ $\boldsymbol{\alpha}(t)$ and $\boldsymbol{\beta}(t)$ so that the generalized function$J_G = J_G(\mathbf{J}(\mathbf{x}(t),\ \mathbf{u}(t),\ \boldsymbol{\nu}(x(t), t),\ \boldsymbol{\xi}(t)))$ achieves its extremal values (e.g., profit, service level, or sales).

Different degrees of human-AI collaboration can define which blocks in Fig. 8 are controlled by a human, what is controlled/adjusted automatically, what is AI-driven, and where a human-AI collaboration takes place.

One essential aspect in ensuring digital twin validity and accuracy is model adaptation (Fig. 9).

Models are fed and—if needed—adjusted with data from real objects. A bidirectional reflexion can be observed—some models enhance and develop other models. In particular, we distinguish between models of supply chain adaptation and models of model adaptation. In addition, AI models for learning the environment and replicating human behaviors and decision-making rules are part of digital twin modeling.

4. Two approaches to building and adaptation of digital twins

In this section, we elaborate more detailed on one specific phenomenon revealed in Section 2, namely the observability of a physical object vs. ecosystem observability. We argue that there are two main approaches to building digital twins: object-driven (i.e., top-down) and data-driven (i.e., bottom-up).

4.1. Object-driven approach

The object-driven approach is more traditional and can be used subject to the static nature of systems to be digitally copied. This approach means that a human is capable of observing a physical object (say, a manufacturing part) and can create its digital replica (Fig. 10).

The object-driven digital twin design begins with observing the physical supply chain. Firms in the upstream and downstream networks and the flows between them are recorded. On this basis, a digital supply chain map, supply chain models, market development, and risk scenarios are defined. Through validation, the digital twin accuracy is estimated to ensure the digital models are consistent with the physical entity, its policies, and behaviors [61].

Data from both the physical supply chain and digital ecosystem are used for detection, monitoring, and feedback functions (e.g., disruption detection, process adaptation, and digital twin adaptation). Through analysis and AI algorithms, planning and control decisions are taken. Learning, update, and adaptation cycle supplement the decision-support process in object-driven digital twins, ultimately resulting in new knowledge.

4.2. Data-driven approach

The data-driven approach takes a bottom-up perspective. It presumes that a real object is not fully observable, and the object is subject to structural and process dynamics changing its systems and operations over time. In this case, we talk about a data-driven and knowledge-driven (rather than object-driven) digital twin building. Digital twins are not "built" but emerge from data, attributes, and knowledge about a system or phenomenon. In this way, they help humans recognize, understand, and observe the systems they have and manage (e.g., through a data-driven supply chain mapping), and – most importantly – digital twins adapt in a decentralized way following the system dynamics and evolution over time (Fig. 11).

One particular challenge is the continuously changing structure of networks and processes. In other words, supply chains are characterized by structural and process dynamics [60]. Building digital twins for such systems can be complicated when using a top-down (i.e., object-driven approach) approach. That is why we favour the bottom-up, decentralized, data-driven and knowledge-driven approach for digital twins.

The bottom-up (i.e., data- and knowledge-driven) approach to digital twin building can be translated to the next level, i.e., digital twin -based model building. In contrast to traditional simulation models which humans build based on their knowledge about the system, which can be subject to incompleteness and inaccuracy), digital ecosystems and digital twins can automate the process of model building and – most importantly – model adaptation.

The following formalization of the data-driven approach to a digital twin design can be proposed using the multi-structural dynamics theory described in [60,62]. The ecosystem data are classified as structures$G = \{ G_\chi, \chi \in NS \}$ of different types such as organizational, financial, and information. To interconnect the structures, a *dynamic alternative multigraph* $G^t_\chi = \left\langle X^t_\chi, F^t_\chi, Z^t_\chi \right\rangle$ can be defined, where the subscript χ characterizes the supply chain design structure type, the time point t belongs to a given set T; $X^t_\chi = \left\{ x^t_{<\chi,l>}, l \in L_\chi \right\}$ is a set of elements (i.e., firms) in the structure G^t_χ (the set of dynamic alternative multigraph vertices) at the time point t; $F^t_\chi = \left\{ f^t_{<\chi,l,l'>}, l, l' \in L_\chi \right\}$ is a set of arcs of the dynamic alternative multigraph G^t_χ and represents relations

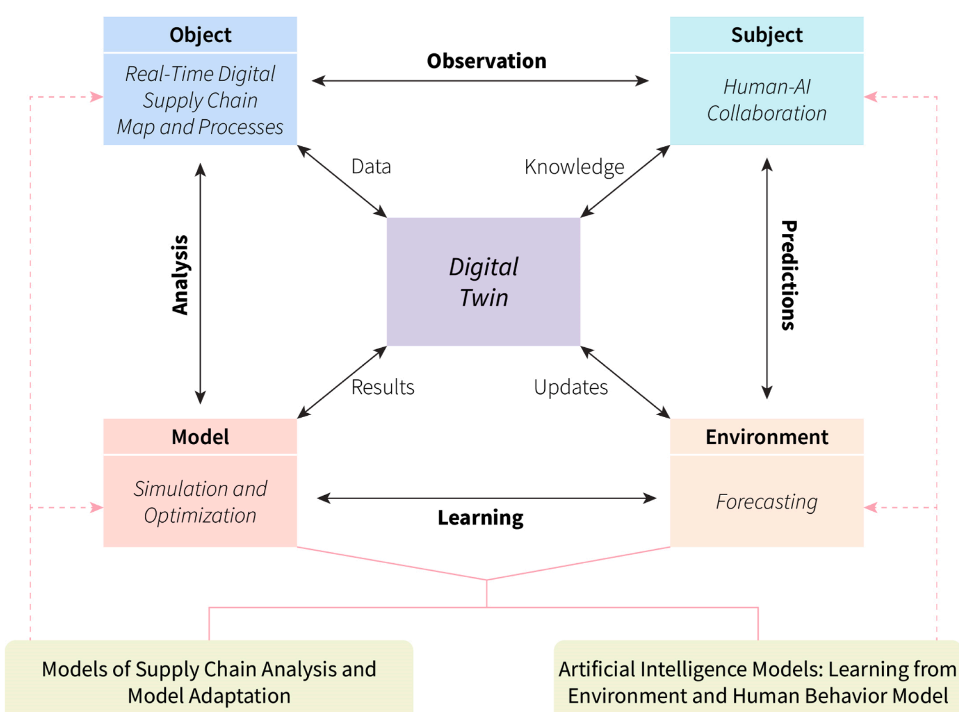

Fig. 9. Modeling of digital twins.

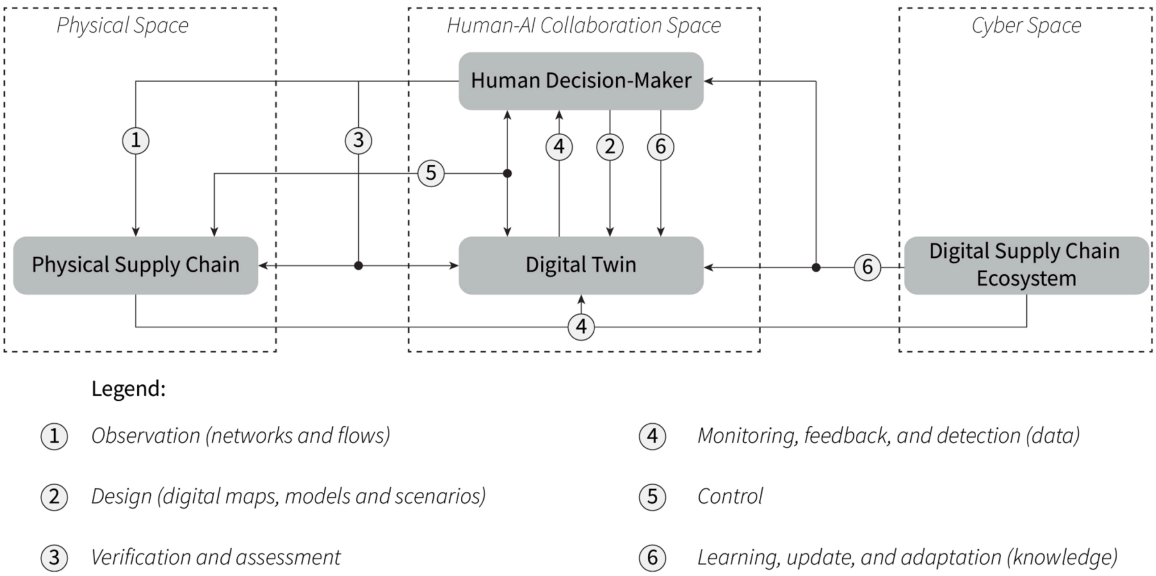

Fig. 10. Object-driven approach to digital twin design.

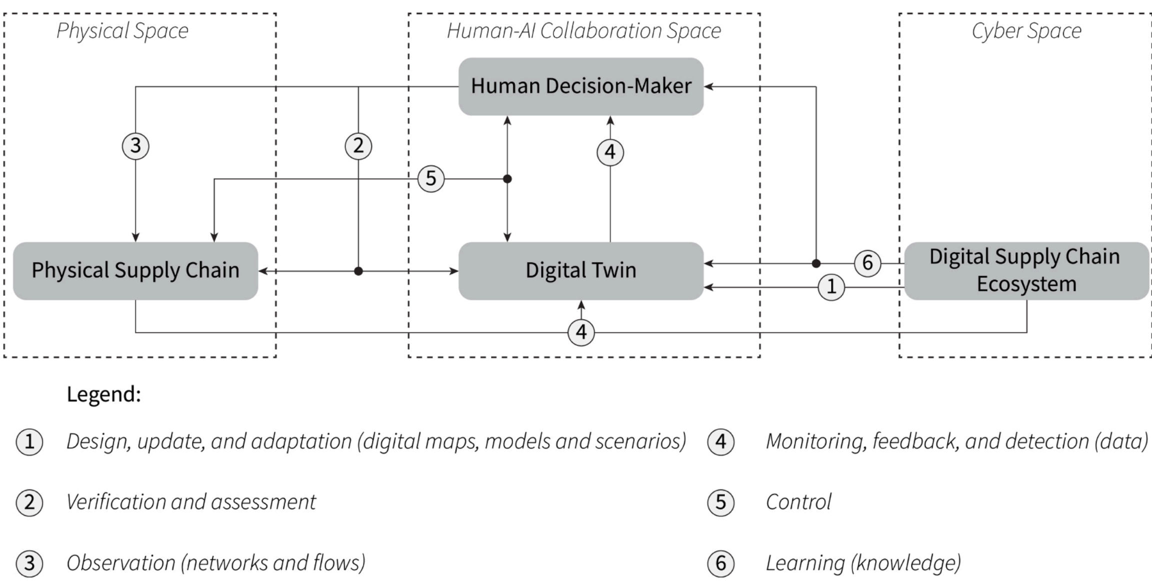

Fig. 11. Data-driven approach to digital twin design.

between the dynamic alternative multigraph elements at time t; $Z^t_\chi = \left\{z^t_{<\chi,l,l'>}, l, l' \in L_\chi\right\}$ is a set of parameters that characterize relations numerically (e.g., inventory and capacities).

To address the dynamic changes in supply chain structures (e.g., new suppliers), a set $S = \{S_\delta\} = \{S_1, \ldots, S_{K_\sigma}\}$of the supply chain multi-structural macro-states in dynamics is formed. Transitions from one multi-structural state to another one can be expressed by means of the mapping $\Pi^t_{<\delta,\delta'>} : S_\delta \to S_{\delta'}$. Now, the problem of the physical supply chain recognition from digital ecosystems can be viewed as a selection of multi-structural macro-states $S^*_\delta \in \{S_1, S_2, \ldots, S_{K_\sigma}\}$ and transition sequence (composition) $\Pi^{t_1}_{<\delta_1,\delta_2>} \circ \Pi^{t_2}_{<\delta_2,\delta_3>} \circ \ldots \circ \Pi^{T_f}_{<\delta',\delta>}$, $(t_1 < t_2 < \ldots < T_f)$ under some criteria of effectiveness, e.g., service level and costs.

5. Cyber-physical supply chain framework

In this section, we first outline a generalized framework of the cyber-physical supply chain comprised of a digital ecosystem, digital twin, human-Ai collaboration space, and the physical supply chain (Fig. 12). Next, we describe potential scenarios for deploying the proposed framework.

5.1. Framework

Merging the analysis of Sections 3 and 4, our framework integrates digital ecosystem, digital twin, human-AI collaboration space, and the physical supply chain (Fig. 12).

Essentially, the cyber-physical supply chain framework is based on an interplay of a digital supply chain ecosystem, digital twin, and human-AI collaboration space. Data- and knowledge-driven digital twins and model building refers to the capability for automatic generation and adaptation of models (e.g., simulation models). That is, instead of having an expert to construct a model based solely on their knowledge of the system, it involves enabling the system to build its model and, more importantly, adapt this model dynamically based on

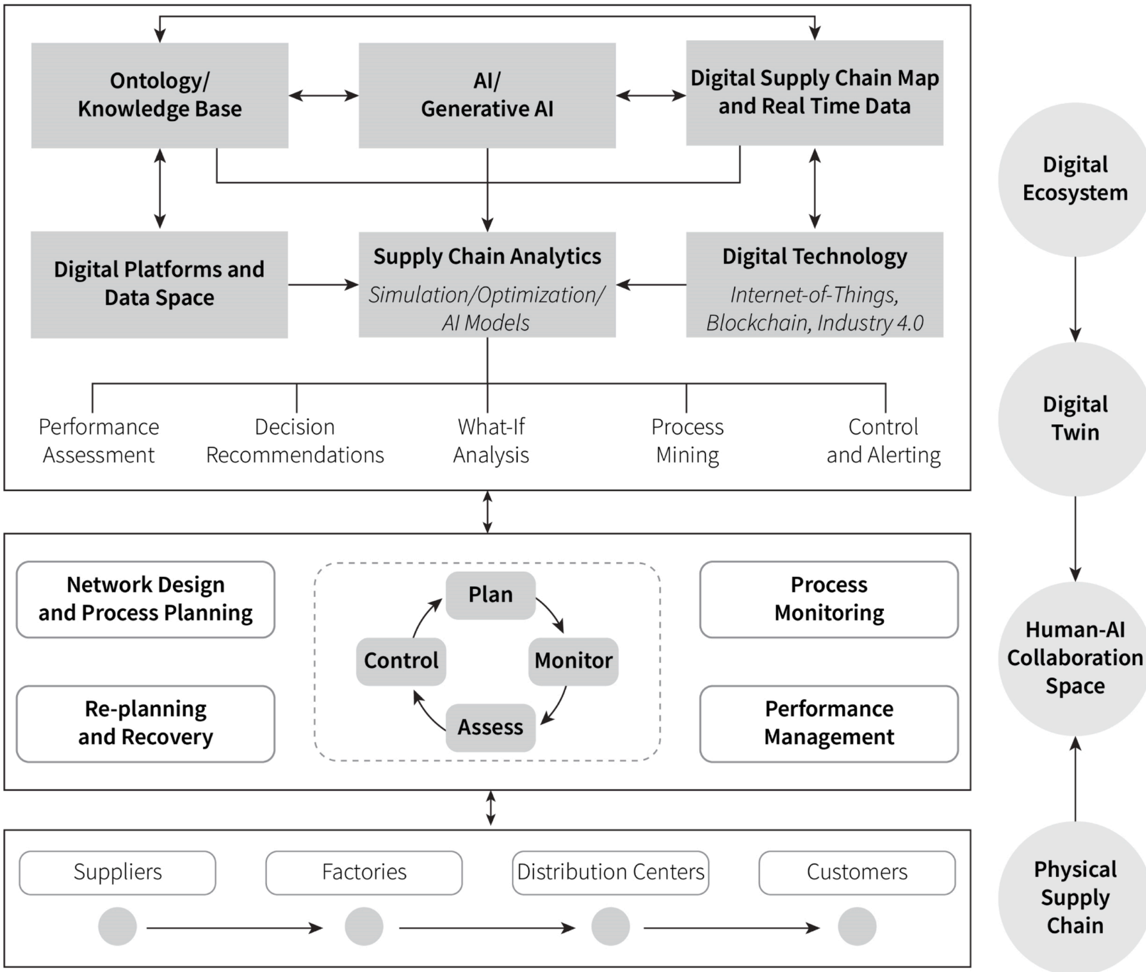

Fig. 12. Cyber-physical supply chain framework.

evolving knowledge (e.g., using a combination of ontologies and generative AI) and constantly updated data.

Furthermore, it is not just about building models, but also about automatically generating scenarios for modeling (e.g., disruption and crisis scenarios) and process mining. Overall, the framework encompasses a combination of observation and control tasks integrating a priori knowledge (e.g., experts and ontologies) and knowledge update (i.e., object identification). In the data-driven approach, the following procedure is used. Digital twin is formed and updated through data and knowledge from the digital ecosystem. Supplemented by human knowledge, verification and assessment take place leading to the recognition and control of the physical supply chain.

5.2. *Application scenario 1: supply chain stress testing*

We now describe a potential application of a digital ecosystem-based

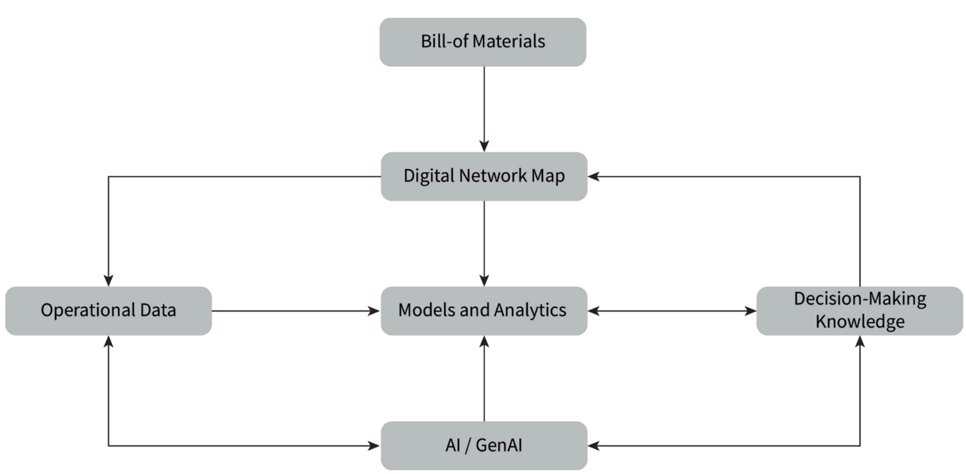

Fig. 13. Digital twin deployment for resilience analysis.

cyber-physical supply chain framework for resilience domain. According to McKinsey report by Alicke et al. [63], the interest in AI-based supply chain tools and simulation is increasing in companies. When modeling supply chain resilience and stress testing, two main issues arise: (i) how to generate disruption and crisis scenarios and (ii) how to ensure model adequacy, accuracy and completeness [64–68]. Digital ecosystems and the framework proposed can be useful for both questions (Fig. 13).

First, a knowledge base of previous disruptions can be combined with generative AI to construct future crisis scenarios and perform stress tests for realistic settings. Second, real-time data allows process mining and model adaptation to a current situation. Fig. 14 illustrates the procedure.

Consider a practical scenario. A tariff chaos at the beginning of April 2025 has wreaked havoc in supply chains across the globe. Digital supply chain ecosystems can help in network discovering, model building and model adaptation. They provide a tangible improvement in decision-making support for performance assessment, AI-based decision recommendations (e.g., for recovery policies after a disruption), what-if testing, and alerting about disruptions [69].

A practical scenario of supply chain stress testing using a digital twin involves mapping the supply chain structure, developing disruption scenarios or monitoring real-time external data, deploying simulation and optimization models to analyze disruption impacts, and saving experiences and learning in the knowledge base of the digital twin for future disruptions. Following [23], the digital supply chain twin use scenario for stress-testing and resilience analysis can be illustrated as follows. The stress-testing scenario begins with disruption identification, which can be based on historical data or even real-time events. Risk data are then mapped with the supply chain footprint. In case of overlapping disruptions with supply chain elements (firms and/or logistics flows), the simulation and optimization models are used to identify performance impact.

Digital ecosystem-based approach can aid in identifying the root causes of disruptions and the ripple effect (i.e., trigger points), and not only solely focusing on generating possible scenarios. The mechanism behind the trigger point identification is based on simultaneous consideration of both material and information flows. Finally, digital ecosystems can help illuminate the digital shadows and add missing information pieces in the digital twins and models, especially in deep tier upstream part of the supply chain. Indeed, while firms are frequently able to develop accurate digital twins of their internal processes and Tier-1 (sometimes even Tier-2) suppliers, their do not have any data about deeper tiers. Here ecosystems can help in network discovery [70]. Such a multi-tier digital twinning can help understand requirements on data and decision-making support at different echelons of the supply chain. AI-driven digital twins can evaluate vast amounts of real-time data. Working like navigators, they can generate and simulate "what if" scenarios tailored to different sectors, suggesting strategic and operative courses of action, whether redesigning the supplier base, using a co-manufacturer, or absorbing tariff costs through demand-supply reallocations.

5.3. Application scenario 2: supply chain collaboration

The role of digital twins in fostering collaboration among supply chain partners is vital [71]. Therefore, a detailed examination of how digital twins facilitate real-time data sharing, improve communication, and enhance visibility across the supply chain is important for validating the proposed frameworks [72]. In this section, we show how digital

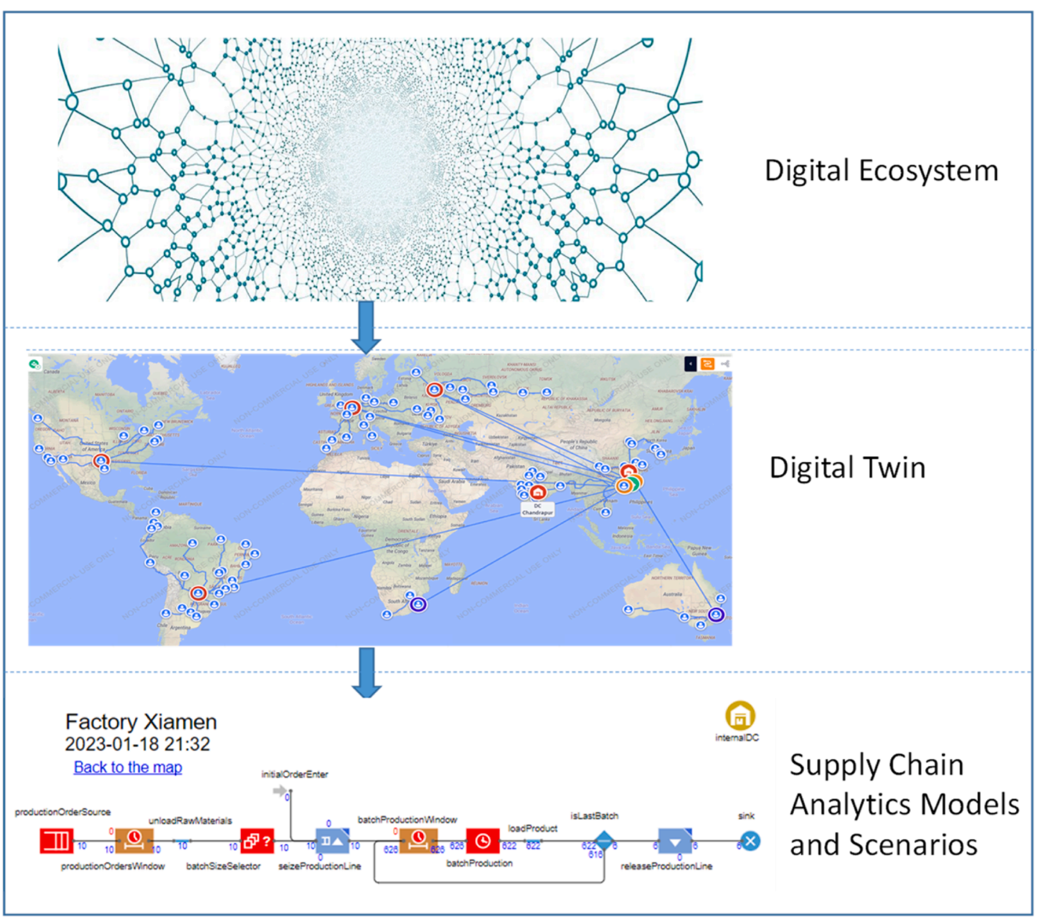

Fig. 14. Data-driven building of a digital supply chain twin.

twins can contribute to a more transparent and efficient supply chain ecosystem using an architecture under development in the CERERE [73] project.

CERERE's (Cereals REsiliency REvolution for agile supply chain management in the Mediterranean) major goal is to increase the resilience and ensure the viability of cereal supply chains and related food systems in MENA (Middle East and North Africa) countries. CERERE technology is based on the design and development of a SaaS platform (the CERERE platform) (Fig. 15). The CERERE technological framework includes seven major parts:

- an open-source middleware and data model for smart agriculture, based on FIWARE and providing specific digitalization services assuring interoperability, scalability, and re-usability;
- a persistent multi-scale and multi-paradigm simulation-based digital twin;
- an AI-based intelligent nerve centre that works concurrently with the simulation-based digital twin and orchestrates the cereal's intertwined supply network with agility and flexibility and a cognitive human interface;
- a starter kit for smart farming based on the IoT to integrate new farmers and smallholders in the CERERE network and create the digital counterpart of the crops;
- an early warning system for supply network vulnerability prediction based on data fusion of real and simulated data;
- a front-end based on web/mobile applications to enable individuals and organisations with low digital competencies or lack of infrastructure to join the digital Mediterranean cereal intertwined supply network efficiently;
- a distributed data fabric architecture for connecting multiple data sources and a situation awareness module.

From a technological point of view, CERERE adopts Open Source standards (e.g., FIWARE) and existing off-the-shelf Free and Open-Source Software (FOSS) components. While FIWARE middleware acts as a communication mechanism, it also serves as a broker to collect all the data the intelligent nerve centre (INC) needs to increase resilience.

IoT Starter Kit aims to create a digital counterpart for farmers in the digital cereal supply network. The IoT Smart Farmer Starter Kit represents the source of real data about crop growth and key agronomic parameters (e.g., humidity), which are measured in real-time, providing reliable data to generate potential crisis scenarios (e.g., a decline in wheat supply because of unfavorable weather conditions). It is ultimately a tool for monitoring crop yield, farming practices (e.g., use of conventional or organic practices), and other useful factors for cereal trade. Such information will be used to gain situational awareness and match the demand with supply.

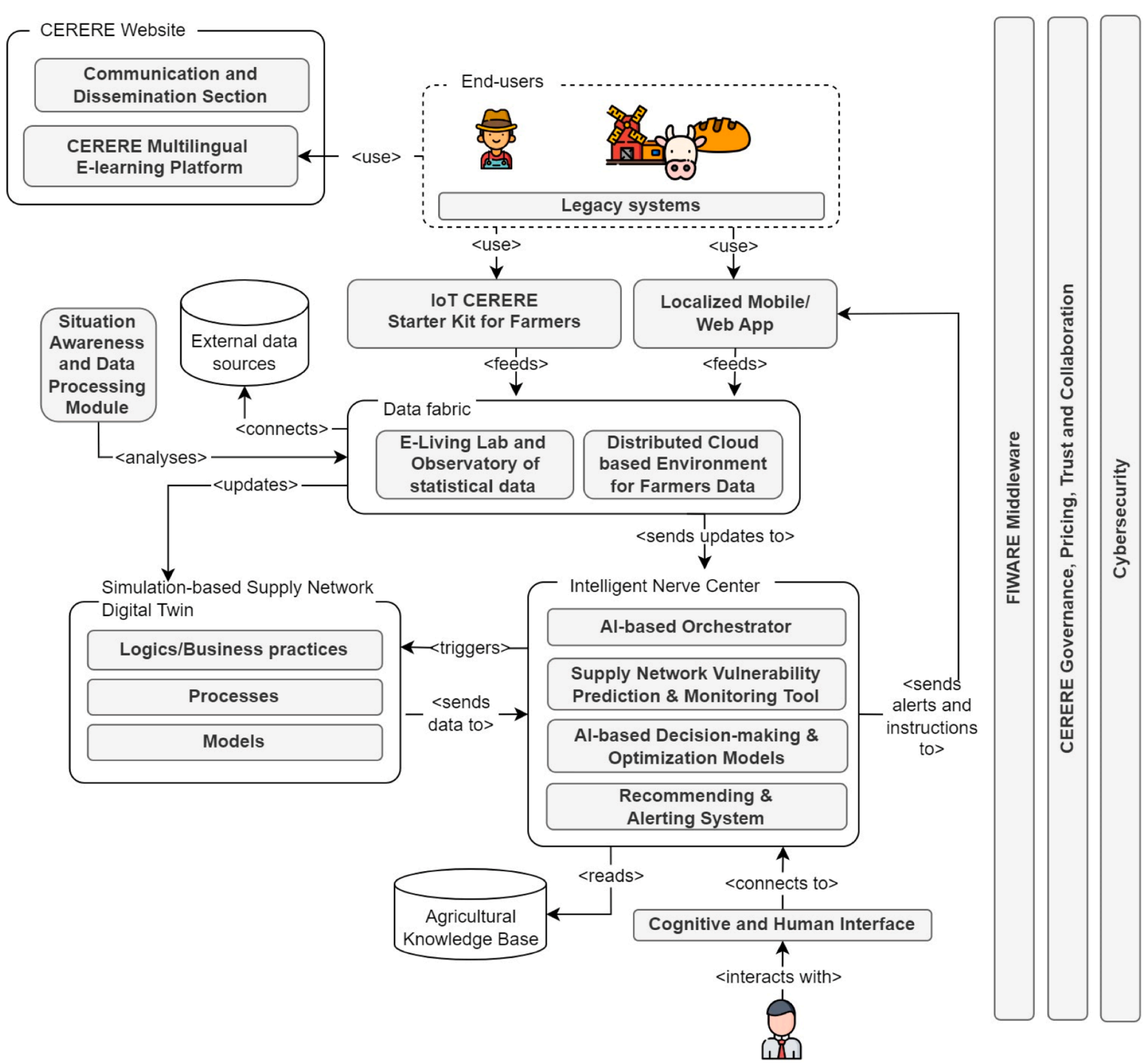

Fig. 15. CERERE technological framework.

Web Application for Digital Twin Commitment is being developed as a tool for supply chain players to create their digital counterparts in the collaborative digital ecosystem. The web app aims to allow the end-users to upload all aspects of cereal trade, including warehouse data, transportation data, (inter)national certifications or certifications compliant with precepts or local rules. The app will also provide services for integrating existing systems, such as enterprise resource planning (ERP) software, warehouse management systems (WMS), and transportation management systems (TMS), with the CERERE platform. Using d*ata fabric and external data sources*, CERERE connects with existing data sources (e.g., public databases and services and enterprise systems) and platforms for disruption/threat detection and early warning, looking beyond data coming directly from supply chain players through the IoT starter kit and the web app. This includes meteorological data, climate data, land/soil biodiversity degradation data, business data, government data, socio-economic data, and inventory/logistics data market data, such as the Agricultural Market Information System (AMIS). To this end, different data sources are integrated into a single architecture, called data fabric, which enables end-to-end integration of various data pipelines and cloud environments.

Situation Awareness and Data Processing Module is used for complex data interpretation tasks such as extracting data from images captured by the cameras in the CERERE starter kit for farmers, and detecting anomalies in multivariate time series obtained from sensors and external data sources (such as humidity, temperature, and grain prices).

Early warning system for supply network vulnerability aims to generate predictive insights and alerts about threats and possible disruptions in a risk-based fashion. The tool does not aim to forecast the next threat or disaster but to continuously monitor the robustness of the network and its capability to survive disruptions or readapt quickly. Both external disruptions (e.g., market trends, seasonality, climate and meteorological events, regional conflicts, pandemics) and internal disruptions (e.g., transportation delays, poor storage and product contamination, crop yield reduction, inefficiency, crop diseases) can be considered. The system will leverage data fusion to detect potential vulnerabilities in the supply network as it will use data from the fields (acquired through the IoT Starter Kit), business data (acquired through the web app), and external data sources connected in the data fabric. The tool will continuously monitor the supply network risk profile and continuity through simulated stress tests or risk assessments using the supply chain simulation model.

The *intelligent nerve centre* (INC) empowers agri-food supply chain actors to sense and respond enabling smart, rapid decision-making through automated and augmented support. It includes an intelligent prescription engine to recommend operational action plans to restore a higher resilience profile in case a vulnerability is detected. The system is more than a procurement intelligence platform, allowing better sourcing or decision-making related to commodity management. It can also provide insights about well-informed and trustworthy actionable plans in response to potentially disruptive supply/distribution vulnerabilities. This includes root-cause analysis, the definition of alternative solutions, simulation-based optimization and digital twinning, what-if analysis, augmented decision support (e.g., recommend next-best action), and automated workflows. An AI-driven recommendation engine helps derive operational instructions for the supply chain players, thus coordinating Med-wide proactive responses to supply chain disruptions. Automated and targeted action plans for the supply chain players will be generated to build/restore resilience and operational actions to pursue (e.g., how should I reorganize the flows?). This module will integrate all the models into a prescriptive system that will control and orchestrate the collaboration among actors in the intertwined supply network.

Simulation-based Supply Network Digital Twin is enabling the INC to find possible vulnerability areas and test and validate candidate solutions. The digital twin is not only the "twin" of supply chain processes but also of the different farmers, individual businesses, and companies of the intertwined supply network. A digital model of the network is developed using simulation Anylogic and anyLogistix. It provides the following capabilities: supply network configuration, forecasting, scenario analysis, analysis of performance dynamics under disruptions, data visualization, and exploration. In future developments, the digital twin will be fed with real-time data, constituting a faithful representation of the supply network and allowing both real-time (online) decision support and what-if analysis.

Cognitive Human Interface & Governance aims to recommend the right action plan and convincingly convey the action plan to the smallholders or cereal businesses. The goal is to provide a more user-friendly and efficient way for humans to interact with complex digital twin models, facilitate real-time decision-making and problem-solving, and enhance the trust in solutions generated and tested by the INC. To this end, human-in-the-loop approaches coupled with reinforcement learning to embed human feedback into the recommendation engine and explainable AI methods will be adopted.

6. Discussion and conclusion

Data-driven approaches and digital technologies increasingly support decision-making in supply chain management. In practice, supply chains are often no longer seen as a network of companies, but from a data perspective. When building digital twins for supply chains, several problems arise, e.g., (i) how to ensure digital twin adequacy, accuracy, and completeness with regard to the physical supply chain and (ii) how to adapt the digital twin to changes in the physical supply chain. In this paper, we discuss two approaches to building digital twins – object-driven (i.e., top-down) and data-driven (i.e., bottom-up).

When managers can observe the supply chain, a digital can be built using the top-down approach. This approach means that a human is capable of observing a physical object and can create its digital replica. The bottom-up approach takes a different, data-driven perspective. It presumes that the real object is not fully observable, and moreover, the object is subject to structural and process dynamics changing its systems and operations over time. In this case, we talk about a data-driven and knowledge-driven (rather than object-driven) digital twin building.

Essentially, digital twins are not "built" but rather emerge from data, attributes, and knowledge about a system or phenomenon. In this way, they help humans recognize, understand, and observe the systems they really have and manage (e.g., through a data-driven supply chain mapping), and – most importantly – digital twins adapt in a decentralized way following the system dynamics and evolution over time. Models of real objects and policies for their planning and control created by human knowledge can be adjusted through digital twins based on data received from real objects. This data is fed as input, fueling models and policies to adjust their rules and constraints. As such, a bidirectional reflexion can be observed when digital models develop physical models, and vice versa. Depending on who has the most complete information about a physical object – an AI agent in a digital twin or a human in the physical space, decision-making can be performed in a human-AI collaboration fashion. We contextualized the practical application of both approaches using examples of supply chain resilience.

Digital supply chain ecosystem notion proposed in this paper extends the existing concepts of digital twins. A digital ecosystem combines various types of models, such as optimization, simulation, visualization, generative AI, ontologies into a unified framework. This comprehensive approach allows for complex analysis and decision-making. Digital twins are generated and adapted in digital ecosystems representing physical systems and objects in a data- and knowledge-driven manner. Specifically, we elaborated on how simulation, digital technologies, and AI can be combined to achieve a principally new quality of modeling and decision-making support in supply chain management.

Digital ecosystems can be instrumental in building the capability for automatic generation and adaptation of models. That is, instead of having an expert construct a model based solely on their knowledge of the system, it involves enabling the system to build its model and, more importantly, adapt this model dynamically based on evolving knowledge (e.g., using a combination of ontologies and generative AI) and constantly updated data.

Moreover, ecosystems help in building models, automatically generating modeling scenarios (e.g., disruption and crisis scenarios), and identifying trigger points of disruption waves. Essentially, it encompasses a combination of observation (i.e., object identification) and control tasks. We contextualize the application of digital ecosystems using examples of supply chain resilience, ripple effect, and stress testing.

Finally, the strategic role of digital twins and ecosystems should be highlighted. In an era of geopolitical tensions, supply chains face unprecedented risks [74,75]. Digital twins could enable organizations to simulate various geopolitical scenarios, analyze potential risks, and devise strategic responses. By visualizing these complex dynamics in a virtual environment, companies can make more informed decisions that enhance their resilience in the face of unknown-unknown uncertainty.

Before concluding, we stress the importance of applying our proposed conceptual and formal models in different use cases for further validation and specification. Digital twins – while sharing a set of common principles across industries – should be grounded in domain knowledge, business rules, and physical constraints while being flexible enough to adapt to changing conditions. This ensures their recommendations are both innovative and practically feasible.

Digital twins are a multidimensional phenomenon integrating organizational, technological, management, and modelling perspectives. Future research in this area is inherently multidisciplinary and will be framed by management, computer science, industrial and control engineering, and operations research. For example, the integration of simulation with quantum computing, development of AI agents for automatic decision-making, scalability of digital twin network, and cybersecurity threats encountered by digital twins are topics of future research interest. Moreover, empirical research can contribute to the ecosystem-based digital twin perspective by discussing emerging challenges and risks these systems introduce within organizations.

Addressing potential barriers to digital twin implementation is as important as defining scenarios for practical implementations. Barriers can include but are not limited to cyber-security issues [76], difficulties with obtaining visibility in deep-tier networks [70], and AI hallucination (Sun et al. 2024). The latter is especially important for intelligent digital twins with AI agents. Responses generated by AI may contain false or misleading information presented as facts and used for decision recommendations. This is a general problem for all generative AI applications and an underdeveloped research area in supply chain digital twins with human-AI collaboration. In this setting, the importance of combining expert knowledge and AI should be strengthened to avoid automatic decisions based on wrong AI recommendations. An AI agent is a decision-making support, not a decision-maker. Human knowledge is essential to avoid the creation of an AI-generated knowledge domain that is not verified and may contain – and most adversely distribute – wrong knowledge and facts, which would be fatal for our society.

CRediT authorship contribution statement

Dmitry Ivanov: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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