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Implementing Digital Twins in Supply Chain Management: A Maturity Model ⋆

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Abstract: Integrating Digital Twins (DTs) within supply chain management offers transformative potential for optimizing operations, enhancing decision-making, and fostering resilience. However, existing literature often lacks practical insights into assessing their maturity. This paper addresses these gaps by proposing a comprehensive Maturity Model (MM) tailored for supply chain DT development. The proposed MM is applied to real-world case studies, highlighting its utility in evaluating DT readiness and guiding implementation. Key challenges, including modeling capabilities, data and system integration, and stakeholders' collaboration, are discussed alongside strategies for overcoming them. This research provides practitioners with actionable insights for building robust DT architectures, enabling organizations to leverage the full potential of digital transformation while ensuring scalability and sustainability.

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Keywords: Digital Twin, Supply Chain Management, Maturity Model, Data Integration, Real-Time Decision-Making, Digital Transformation.

1. INTRODUCTION

A digital twin (DT) can be defined as a "virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning, and reasoning to help decision-making" (Le and Fan, 2024). DT are predominantly used for designing, modelling, visualizing, testing, and implementing new ideas without disrupting the current process. The application of Digital Twin technology extends beyond conceptual frameworks to practical implementations, particularly in supply chain management, where it is possible to integrate sensors and other data handling technologies (e.g., Internet-of-Things) to several critical phases of supply chains (e.g., orders arrival timestamps, shipping tracking), generating insights into the performance of a physical supply chain, identifying potential issues or bottlenecks (Wang et al. 2022), supporting risk mitigation (Le and Fan, 2024) and including some benefits such as the optimization and improvement of customer service and traceability, costs reduction, and profits increasing (Lugaresi and Jemai, 2023).

Based on this premise, this research aims to address critical gaps in the study and application of Digital Twins in supply chain management (DTSCM). Despite growing interest, the literature predominantly focuses on developing DTSCM frameworks or their implementation, with limited exploration on evaluating the level of integration among stakeholders, data sources and systems and the main strategies towards the implementation of a full DT. Additionally, decision-makers face difficulties in understanding how a DT can be applied to their specific needs. A lack of performance assessment of the DTSCM levels of maturity then renders the integration of DT technologies into supply chains an actual challenge and hinders their practical adoption.

This study aims to analyze supply chain DTs through a Maturity Model to evaluate their stage of implementation. The objective is to offer businesses a decision support framework to assess the necessity of DT adoption, identify suitable technologies, and optimize their integration for sector-specific applications. Specifically, this research seeks to address the following questions::

RQ1. How can a Maturity Model be designed and implemented to evaluate the readiness and effectiveness of Digital Twins in supply chain environments?
RQ2. What are the key challenges that must be addressed to achieve higher levels of maturity in the implementation of DTSCM?

The structure of the paper will consist in a literature review section (Section 2) followed by a methodology section highlighting the approach towards the DTSCM maturity model development as well as its dimensions and

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levels (Section 3). Then, the final MM based on existing use cases will be presented in Section 4. Finally discussions and conclusion sections will close the paper (Sections 5 and 6).

2. LITERATURE REVIEW

2.1 Implementation process of Digital Twins in the Supply Chain

The DTSCM implementation steps are closely related to its architecture, which is often composed of hierarchical layers. Layers categorize and structure the functional aspects of a supply chain, while hierarchy levels organize and simplify the complexity within each layer, enabling modularity and scalability (Le and Fan, 2024). Le and Fan (2024) propose an holistic approach with three closely interrelated layers of the DT, namely physical, digital and communication layers. Freese and Ludwig (2024) organize the DTSCM development across five layers: i) a data layer; ii) a technology layer to capture, process and display data; iii) an application layer comprising the scope the DTSCM in terms of purpose (e.g. monitoring and control) and KPIs; iv) a workflow logic layer containing the processes in which the digital twin is integrated and finally v) a structural model layer depicting the structure of the supply chain within the DTSCM, including actors and physical assets. This architecture is fundamentally grounded in SCM theory and application and thus provides a significant development in terms of implementation steps and maturity levels in the context of DTSCM. A six-layer architecture for a manufacturing DT is also proposed by Redelinghuys et al. (2020). Additional layers are presented in this paper, namely local and cloud repositories and a "Data-to-Information Conversion Level", or IoT Gateway. This architecture is specifically developed to work with open communication protocols and thus provide a suitable way to integrate with existing legacy systems and supports the implementation of the DTSCM in operational terms. The DTSC implementation literature acknowledges that during the DTSCM implementation certain elements must be given significant consideration. Robust infrastructure, data connectivity, and skilled personnel are prerequisites for creating and operating DTs (Patil et al., 2024). Beyond data connectivity, effective data management is a fundamental pillar for the successful implementation of Digital Twins, as the quality and reliability of information directly impact the accuracy of monitoring, simulations, and decision-making (Lanzini et al., 2024). In their use case application, Redelinghuys et al. (2020) mentions latencies between layers as well as significant lags when updating values in the cloud server database as operational hurdles that affect the ability to emulate fast-changing process parameters in real-time. Using readily available technologies and services, such as cloud-based database services, may reduce the expertise required to develop a digital twin (Redelinghuys et al., 2020). It is worth mentioning in fact that organizational challenges arise when implementing a DT in such systems, and thus organizational leadership can support the DT implementation by promoting a culture of innovation and facilitating cross-functional collaboration to ensure the seamless integration of DTT into operational processes (Patil et al., 2024).

2.2 Maturity Models

In general terms, the concept of maturity can be defined as the state of being perfect, complete and ready or more specifically, as a measure to evaluate the resources used by an organization (Kucińska-Landwójtowicz et al., 2024). A Maturity Model (MM) is a tool that can be used to evaluate specific domains against a benchmark (Santana Tapia et al. 2008). It helps to identify technological or organizational potentials to improve desired outcomes (Uhlenkamp et al., 2022). Typically, maturity models define a series of levels or stages, each representing a higher degree of sophistication, efficiency, and optimization (Warnecke et al., 2019). A MM typically has three common components. First, a set of levels describing the development of a process. Every level is sequential with a hierarchical progression, ranging from the most basic degree to the best practices. To determine the maturity level, an evaluation is carried out considering several criteria that are divided into categories. The criteria are the second component and the categories (called attributes) are the third component of a MM (Guerra et al., 2024). MM have been applied to evaluate supply chain risks in different industry fields and to companies of different size to stimulate the development of capabilities required to advance from one stage to another (Dellana et al., 2022). Regarding the maturity levels of DT, the literature has introduced it based on the sophistication of the implemented DT, outlining the progressive levels of DT development (Hu et al., 2023). In the development of Digital Twin model, Liu et al. (2024) present a Digital Twin Maturity Model (DTMM), identifying five different steps related to the DT maturity. This model describes the conceptual domain, capabilities and developmental progression of DT, integrating the every objectives with the capabilities and the technologies. In the specific context of DTSCM, maturity levels are briefly mentioned in Freese and Ludwig (2024). At a low maturity level, only basic descriptive functions are achievable. At the diagnostic maturity level, it becomes possible to derive insights and diagnoses from historical data. The predictive maturity level facilitates the forecasting of potential future issues. The prescriptive maturity level, representing the highest stage, enables the digital twin to proactively predict, intervene, and autonomously influence the physical entity. At this advanced level, the integration of actuators, in addition to sensors, is essential. This study is, to the best of the authors' knowledge, the first attempt at evaluating the DTSCM from a MM standpoint.

3. METHODOLOGY

For this research, the steps for the development of a maturity model proposed by Becker et al. (2009) have been used. In particular, the different steps have been revised by the authors according to the research workflow shown in Figure 1.

The problem definition phase have been already reported in Section 2.1 in which the different gaps in implementing DT for supply chain have been discussed and the main objectives and challenges have been proposed. Section 2.2 has reported the comparison of existing maturity models discussing also the common dimensions and common scoring method adopted. Section 4 will present the result of

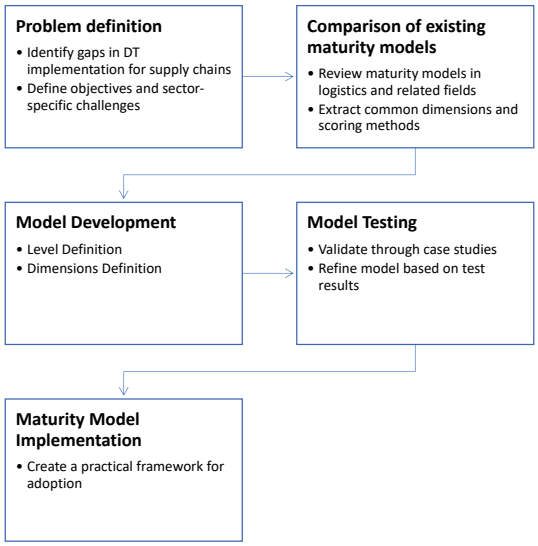

Fig. 1. Research Workflow

the model development in terms of level, dimensions and criteria. In particular the model proposed by Uhlenkamp et al. (2022) has been taken as a reference because it is the second model with the highest number of citations in the scientific literature on maturity models for digital twins. The most cited maturity model for digital twin is the one by Delgado and Oyedele (2021). However, this MM seems to be useful only in the case of built environment and less generalizable, while both Becker et al. (2009) and Uhlenkamp et al. (2022) are more generic and follow a dimensions definition based on the Human-Technology-Organization (HTO) framework that is also very common in maturity models related to Industry 4.0 assessment (Elibal and Özceylan, 2022). The supply chain customization of the model started from the analysis of the 31 dimensions stated by the Uhlenkamp et al. (2022) and their possible relation with the main elements of the supply chain domain.

After the development phase, the maturity model has been tested using case studies from literature, industry practices and use cases where the authors are involved. In particular, the DTSCM has been tested by retrieving information from highly cited papers from the following query launched on the SCOPUS database: TITLE-ABS-KEY ("Digital Twin" AND "supply chain"). Only scientific papers with real DTSCM implementations were considered in the analysis.

4. MATURITY MODEL FOR DTSCM

According with the MM for supply chain risk management proposed by Guerra et al. (2024), a Maturity Model is composed of two elements: levels of maturity (Section 4.1), dimensions or attributes (Section 4.2) and criteria to differentiate between the levels (Section 4.3).

4.1 Levels

Levels are the maturity stages that the dimension assumes (Gastaldi et al., 2018). As highlighted in Section 2.2, four maturity levels of DTSCM are briefly introduced in Patil et al. (2024) but not well defined in terms of dimensions

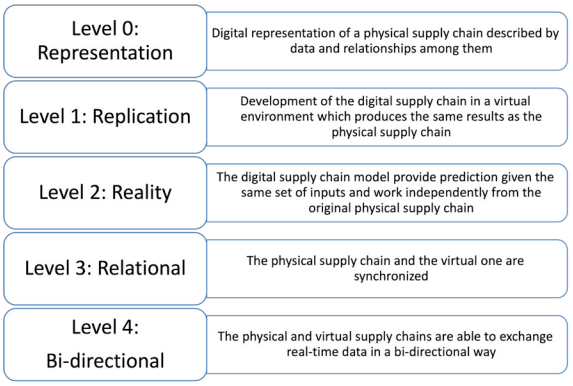

Fig. 2. Maturity Model Levels

Macro-Dimensions	Dimensions	Definition	Reference
Human	Learning capabilities	The ability of personnel to acquire, process, and apply knowledge and skills for implementing and managing DT.	Patil et al. (2024); Le and Fan (2024)
	Stakeholder collaboration	Cross-functional and inter-organizational teamwork enabling smooth adoption of DT technologies in supply chains.	Huang et al. (2024); Ivanov et al. (2019)
	Skills development	Continuous training programs for enhancing competencies in data-driven decision-making and DT management.	Freese and Ludwig (2024); Lanzini et al. (2024)
Technology	Traceability tools	Technologies that enable tracking and tracing of assets and information across the supply chain.	Ivanov et al. (2019); Redelinghuys et al. (2020)
	Digital processes	Automated and streamlined workflows supported by digital technologies.	Le and Fan (2024); Freese and Ludwig (2024)
	Modeling and computing capabilities	Different levels of capabilities to process the incoming information as well as simulation and data analytics methods	Uhlenkamp et al. (2022); Stadtfeld et al. (2024)
	Data and System Integration	Proficiency in deploying and integrating data from different sources, digital tools, platforms, and software for DT.	Lanzini et al. (2024); Liu et al. (2024)
	Update data frequency	Regular intervals at which real-time data is captured and synchronized across DT SC layers.	Redelinghuys et al. (2020); Frazzon et al. (2021)
	Cybersecurity strategies implemented	Measures ensuring the security, integrity, and confidentiality of data in DT-enabled supply chains.	Patil et al. (2024); Haraguchi et al. (2024)
Organization	Supply chain echelon definition	Clear identification and structuring of supply chain layers for effective DT deployment.	Becker et al. (2009); Uhlenkamp et al. (2022)
	Communication procedures among SC actors	Defined protocols for information exchange and coordination within the supply chain.	Lanzini et al. (2024); Freese and Ludwig (2024)
	Modularity of different echelon management	Flexible and scalable management systems enabling modular DT adoption.	Redelinghuys et al. (2020); Uhlenkamp et al. (2022)

Fig. 3. Maturity Model Dimensions

and assessment system. For this research instead the chosen maturity levels are based on the simulation and digital twin capability levels proposed by Wooley et al. (2023), which are then adapted to the supply chain context.

Figure 2 depicts the five maturity levels of digital twin (DT) implementation in supply chain management, progressing from basic digital representation (*Level 0: Representation*) to fully integrated bidirectional systems (*Level 4: Bi-directional*), going through a DT with prediction capabilities that hinge on the same set of inputs while working independently from the original physical supply chain (*Level 2: Reality*).

4.2 Dimensions

A dimension represents the characteristic of an organisation/process or the capability that is measured; Therefore, while maturity models can be one-dimensional, they are more commonly multi-dimensional, providing a structured assessment of a company's capabilities across different domains, each of which can be evaluated independently across scaled maturity stages(Wendler, 2012). Figure 3 contains the results of the dimensions and their definition.

Macro-Dimensions	Dimensions	Level 0: Representation	Level 1: Replication	Level 2: Reality	Level 3: Relational	Level 4: Bi-directional
Human	Learning capabilities	Awareness of DT concepts	Basic knowledge acquisition	Application of DT in limited contexts	Advanced proficiency in DT integration	Mastery and innovation in DT application
	Stakeholder collaboration	Initial stakeholder mapping	Basic collaboration structures established	Advanced collaboration mechanisms	Dynamic collaboration among stakeholders	Fully integrated, real-time stakeholder sync
	Skills development	Ad-hoc skill-building initiatives	Training for specific DT-related tools	Specialized training programs	Comprehensive cross-functional training	Continuous skill innovation programs
Technology	Traceability tools	Minimal data tracking	Simple tracking systems implemented	Advanced traceability with limited integration	Fully integrated traceability systems	Real-time, predictive traceability systems
	Digital processes	Manual workflows digitized	Automated workflows with minimal complexity	Comprehensive digital processes implemented	Synchronization of digital and physical processes	Fully autonomous digital processes
	Modeling and computing capabilities	Basic UML description of SC classes and actors	Simulation models with prediction capabilities over few problems	Simulation-optimization digital models able to treat more KPIs and predict what-if scenarios	Multi-objective advanced data analytics problem solving models implemented	Multi-objective advanced data analytics problem solving models with reinforcement learning capabilities
	Data and System Integration	Limited integration with legacy softwares with few unstructured data sources	Basic platform integration using structured data from few sources	Advanced platform integration using structured data from multiple sources within the SC	Fully integrated DT systems using structured data from multiple sources within the SC and unstructured data from external sources	Self-optimizing digital ecosystem using structured data from multiple sources within the SC and structured data from external sources
	Frequency of data update	Infrequent updates	Periodic updates	Near real-time updates	Real-time updates achieved	Continuous real-time data flow
	Cybersecurity strategies implemented	Basic data protection measures	Initial cybersecurity policies applied	Comprehensive cybersecurity systems	Real-time cybersecurity monitoring	Adaptive and predictive cybersecurity
Organization	Supply chain echelon definition	Echelons loosely identified	Echelons structured for DT adoption	Defined roles and responsibilities	Seamless echelon synchronization	Dynamic echelon management
	SC level communication procedures	Minimal communication protocols	Initial communication structures	Advanced communication procedures	Fully transparent communication	Real-time adaptive communication frameworks
	Modularity of different echelon management	Minimal modularity	Basic modular structures defined	Modular DT components implemented	Modular systems fully operational	Adaptive modular management systems

Fig. 4. Definition of criteria for the dimensions and levels of the DTSCM MM

4.3 Criteria

In this subsection the main criteria identified from findings from the data collection are presented. A full definition of the criteria for all dimensions and levels which is shown in Figure 4 is out of scope of this paper.

Digital Twins (DTs) in supply chains are increasingly supported by *Traceability tools* at varying levels of maturity. Foundational systems require simple tracking from legacy systems like Warehouse Management Systems to replicate the physical object (Ferrari et al., 2023). Intermediate tools, as seen in Lee and Lee (2021), propose the use of IoT sensor data to create virtual assets, such as trucks and modules, although such systems are not yet fully implemented. Advanced levels focus on establishing IoT-enabled smart environments to collect and pre-filter real-time spatial–temporal data (Zhao et al., 2022). These systems utilize BLE tags paired with mobile resources (e.g., trolleys, forklifts, personnel) and deep neural networks to locate entities and ensure spatial–temporal consistency between physical and virtual assets.

Data and system integration play a crucial role in enabling Digital Twins (DTs) for supply chains by connecting internal and external systems, synchronizing data sources, and ensuring actionable insights. Renault integrates its own data with partner ERP systems and public access data, enhancing visibility across suppliers and logistics networks (Stadtfeld et al., 2024). Platforms like JD.COM's DTSC (Wang et al., 2022) synchronize physical supply chains and digital models using network configurations, procurement, transfer, and fulfillment systems, achieving high accuracy in monitoring key metrics. Integration frameworks further simplify communication; for instance, Park et al. (2021) leverage APIs and protocols like Simple Object Access Protocol (SOAP) for loosely coupled integration. More advanced systems such as the DT by General Electric Power adopt advanced data harmonization by consolidating five unconnected ERP systems and managing structured, semi-structured, and unstructured data in a unified data lake. Additionally, this DT integrates third-party data to monitor external influences, such as political and environmental factors (Stadtfeld et al., 2024). A DT by TetraPak also showcases the use of electronic data interchange (EDI) to combine GPS data, weather information, and partner carrier inputs, facilitating accurate, real-time decision-making (Stadtfeld et al., 2024).

Data and system integration are key enablers of *Stakeholder Collaboration* and *Communication Procedures*, promoting real-time communication and reducing inefficiencies. Using local databases may hinder the ability to foster collaboration but does not require significant effort in terms of data conversion and semantics harmonization. Siemens utilizes an Anylogic database as a central repository, updating and sharing input and output entities to facilitate seamless communication across internal systems (Stadtfeld et al., 2024). Marmolejo-Saucedo (2020) also uses local databases in their DT. Renault instead is able to alert all relevant parties in real time, ensuring that all stakeholders are kept informed of critical developments by using CC technologies (Stadtfeld et al., 2024). Similarly, Tetra Pak's integration efforts reduce bottlenecks and miscommunications, particularly in shipment management, improving the coordination between partners (Stadtfeld et al., 2024). Zhao et al. (2022) highlight the benefits of inviting upstream and downstream suppliers to collaborate directly in the industrial park, which not only fosters better communication but also helps reduce delivery costs.

Modeling and computing capabilities are fundamental to the effectiveness of Digital Twins (DTs) in supply chain operations, enabling dynamic simulation, optimization, and decision support. The first steps of a DT maturity involves basic UML depiction of the main SC classes and actors and discrete-event simulation models to represent basic SC processes as well as make prediction on a few subset of SC problems and KPIs (Ferrari et al., 2023; Lagorio et al., 2024). Marmolejo-Saucedo (2020) leverages simulation-optimization methods to generate more system-level KPIs. Zhao et al. (2022) emphasize the importance of algorithms like Dijkstra's for optimizing routes while considering constraints such as time windows and capacity. These capabilities enable DTs to deliver high accuracy in simulating physical supply chains, as seen in JD.COM's platform, which captures key metrics with 96% accuracy, and supports continuous optimization for real-time decision-making. In more complex supply chain models, Wang et al. (2022) demonstrate that optimization and simulation algorithms can be integrated to balance conflicting objectives, simulate different strategies, and evaluate solutions based on various performance indicators like inventory turnover, order fulfillment, and costs. Further advancement envision the use of advanced data analytics methods. Renault utilizes AI to enhance decision-making and predict risks with greater accuracy, improving outcomes for drivers, fleets, and cargo (Stadtfeld et al., 2024). General Electric Power also incorporates AI to refine its operational efficiency, while Siemens applies advanced simulation and data analytics to optimize fleet management, enabling adaptive, data-driven decisions (Stadtfeld et al., 2024).

Learning capabilities within Digital Twins (DT) in supply chain management are essential to continuously improve decision making and operational efficiency. Learning relies primarily on manual data input and basic descriptive ana-

lytics at lower maturity levels. In contrast, at advanced levels, DTs leverage AI-driven predictive models, deep learning techniques, and real-time data harmonization to refine operational strategies and improve adaptability. Organizations investing in DT development must also focus on skill building and knowledge transfer to bridge the gap between technological advancements and workforce capabilities, ensuring sustainable and scalable implementations (Srivastava et al., 2022).

Finally, *Digital Processes* are crucial for automating and streamlining operations, reducing reliance on manual tasks, and improving efficiency. Marmolejo-Saucedo (2020) highlights that data is often collected and uploaded by professionals through spreadsheets or other databases, which can be time-consuming and prone to error. General Electric Power has significantly enhanced its processes by eliminating numerous separate, manually maintained spreadsheets and dashboards, which previously took days to compile, thus speeding up decision-making and improving data accuracy (Stadtfeld et al., 2024). Additionally, this system supports automated scenario testing, enabling the company to evaluate different operational strategies without manual intervention.

5. DISCUSSIONS

5.1 Cross-case analysis

From the use cases analyzed it is clear that several DT dimensions are interrelated and should be driven forward together in order to reach higher levels of maturity of the DTSCM. For instance, advanced modeling methods (e.g., AI) depend on seamless, real-time data integration to support prescriptive decision-making. Data integration also enhances stakeholder collaboration and enable digital processes with automates workflows, reducing the time lag between insights and actions. At higher maturity levels then, DTs enable self-optimizing, autonomous supply chain ecosystems capable of responding dynamically to disruptions and opportunities.

These seemingly trivial results conceals key challenges that the proposed MM brings front and center and that did not receive much attention from scholars in the field of Digital Twins in SCM. For instance, even though having standardized communication protocols fostered by a trusted and aligned network of stakeholders will help overcome the barriers to achieving full data and system integration, open questions remain as to how cybersecurity issues are to be solved, and what are the levels of maturity connected with different cybersecurity strategies. The inherent reliance of DTs on online digital platforms with varying security levels (open, walled garden, and closed), as well as the vulnerability of older, resource-constrained field gateways, further underlines the necessity of robust cybersecurity strategies (Tao et al., 2018). Furthermore, to facilitate the DT advanced data processing and analyses capabilities, its implementation typically relies on cloud storage, where practitioners should take notice of the different level of security between open cloud (least secure), hybrid cloud (medium security), and private cloud (most secure) (Pärn et al., 2024). Finally, real-time data exchange and communications enabled by digital tools inherently amplify vulnerabilities, exposing DTs to potential cyber intrusions and malicious attacks (Pärn et al., 2024).

Furthermore, it is well known that tracing technologies (e.g. IoT, blockchain) play a significant role in overcoming the challenges of data harmonization, and computing capabilities enable advanced data analytics problem solving by the Digital Model of the DT. However, oftentimes there is a steep learning curve for the DT development and thus organizations should also invest in DT development skills and learning capabilities, in order to increase their overall level of maturity.

5.2 Theoretical and practical implications

In terms of theoretical implications, the novelty of this work lies in its first attempt at generalizing the levels of maturity of a DTSCM over multiple dimensions that go beyond the more traditional perspective of a DT as a technology. The definitions of the levels of maturity here proposed may help practitioners and scholars to take more informed decisions at the pre-adoption or pre-implementation stage, particularly in terms of the simulation software to use, which will affect the computing capabilities as well as dictate which skills to develop (Lanzini et al., 2024); the choice of the reference object, meaning which processes or actors of the SC are modeled by the DT, which will drive the path towards higher levels of data and system integration and stakeholders collaboration maturity (Huang et al., 2024; Uhlenkamp et al., 2022). Finally, this MM introduces a definition for the fully developed DTSCM, which can unlock the potential for a system-of-systems approach or better a DT of DTs approach, where multiple DTs are integrated to provide improvement beyond the single company SC. In this sense, creating frameworks that support data sharing within a data ecosystem, such as data spaces, is instrumental.

6. CONCLUSIONS

This paper presented a first attempt at a Maturity Model for Digital Twins in the supply chain management domain of application. The definition of levels and dimensions were taken from previous works on MM in Digital Twins and Supply Chain contexts, and a proposal for defining the criteria for all dimensions at all levels is also outlined in this work. The MM highlighted the strategies for transitioning towards higher level of maturity, focusing on few interrelated dimensions such as data and system integration and stakeholders collaboration. It also outlined some dimensions that could receive more attention in future research such as skills development and cybersecurity strategies. This study has several limitations. First, the maturity model has been tested only on few selected use cases and scientific papers. A proper evaluation of the maturity model will be the subject of future work and will involve extending the analysis to a more encompassing literature review and gaining insights from practitioners and real-life use cases. Second, only the development of the maturity model was included within the scope of this paper. The implementation phase will be developed in future research activities.

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