**Title:** From Warehouse Management Systems to Digital Twins: Transition or Transformation?

**Abstract**

This article presents the development and application of a Digital Twin (DT) evaluation framework and assessment tool. The tool is built upon a comprehensive review of the state-of-the-art literature on DT definitions, standards, frameworks, requirements, and characteristics. Developed using Streamlit, the tool facilitates data collection and survey creation, enabling a structured and iterative assessment of DT maturity. Following the evaluation, a recommendation phase is implemented using a large language model (LLM) trained on the literature underlying the questionnaire, as well as relevant use case studies, to provide tailored guidance when necessary. The second part of this study explores the conceptual and practical relationships between Warehouse Management Systems (WMS) and DTs, investigating whether modern WMS can evolve into full-fledged DTs. To this end, the proposed evaluation framework is applied to contemporary WMS, highlighting key gaps and future directions needed to bridge these two paradigms.

1. **Introduction**

Digital Twins have been adopted across various domains. For instance, in manufacturing, they enable real-time monitoring, optimization, and predictive analytics on production processes (Tao & Zhang, 2017). In smart cities, they support resource optimization and urban planning, while in healthcare, they model patient-specific treatment scenarios (Negri et al., 2017; Ivanov & Dolgui, 2021). Similarly, in warehousing and supply chain contexts, DTs can provide end-to-end visibility of inventory, simulate disruptions, and optimize logistics operations to enhance supply chain resilience (Ivanov & Dolgui, 2021; Negri et al., 2017). Energy systems benefit from DTs through grid management, predictive failure analysis, and energy consumption optimization (Fuller et al., 2020). In construction and civil engineering, DTs enable real-time tracking of infrastructure projects, structural integrity analysis, and the optimization of building management systems (Opoku et al., 2021).

For a tool that is starting to be widely used in different fields, a universally accepted definition remains elusive (Fuller et al., 2020). Several studies highlight the lack of a universally accepted definition of Digital Twins and emphasize the need for an evaluation framework to assess the maturity of DT systems (Boyes & Watson, 2022; dos Santos et al., 2022; Durão et al., 2018; Hu et al., 2023). Research cannot land on a practical definition that captures the technology full specter and use. This definitional ambiguity creates challenges for researchers and practitioners trying to assess whether a system qualifies as a Digital Twin or merely a sophisticated simulation (Tao et al., 2019). Given this ambiguity, there is a need for a systematic evaluation framework that allows researchers and industry professionals to determine whether their developed systems align with the core principles of DT technology. This paper aims to bridge that gap by introducing a DT Evaluation Tool, a structured methodology designed to assess DT systems based on research-driven definitions and requirements. To the best of the authors knowledge the only papers that tackle similar interests are those of Hu et al., (2023), Liu et al., (2024) and Uhlenkamp et al., (2022) who developed maturity models that judge who far developed the DTs are. However, they allow for the respondents the liberty to judge if their tool is a DT instead of interpreting if the systems being evaluated is actually a DT. Uhlenkamp et al., (2022) also developed website that resembles the tool proposed in this paper: <https://dt-maturity.eu>. This website doesn’t give any analysis or conclusions based on the answers of the survey. The application presented in this paper allows to “in a way that doesn’t ask the respondent if their system’s a digital twin” to assess if the system is a digital twin to begin with and then what is the maturity level of the digital twin. It is then equipment with an LLM, GPT, chatbot interface that allows the users to communicate and move towards the DT trained on the all the references used for building the questionnaire and a wide knowledge base of applications papers.

A DT evaluation and maturity model is important to accurately evaluate the maturity level of the system and further pave the ways to develop an advanced DT. The purpose of a maturity model is to evaluate the state or quality of a DT, ensure quality, avoid errors, and assess the capabilities of entities on a quantitative and comparable basis. It is also used to evaluate the deficiencies of existing DTs and provide guidelines for further improvement.

To validate this evaluation tool, we apply it to warehouse management systems (WMS), a field where DTs are increasingly becoming a critical data source for logistics and warehouse optimization. **(Go fetch the WMS paragraph from the other paper).** By testing the tool in a warehousing context, we demonstrate the robustness of WMS’s as a management tool across logistics systems and we pave the way for future WMS applications and their relation to DT. Will it be a transition of a transformation?

The rest paper is structured as follows: Section 2 provides a literature review on the various definitions and fundamental requirements of DTs and Section 3 introduces the DT Evaluation Tool, detailing its modeling approach and key evaluation criteria and analysis.

Section 4 applies this evaluation tool to warehouse management systems, analyzing its effectiveness in assessing DT implementations in logistics.

Section 5 discusses key findings, implications, and limitations before concluding with future research directions.

1. **Definitions of a Digital Twin**

There is a lack of uniformity in the definition of a digital twin, which further emphasizes the need for a standardized framework [1, 2, 3]. DTs are often regarded as the next evolution of simulation, as they involve the creation of a virtual environment that replicates and continuously interacts with the physical system [4]. They can also be perceived as a bridge between the physical and digital worlds, enabling a continuous feedback loop for the optimization of products and processes [5]. With the introduction of the term “digital twin” in 2003 by Grieves, within the context of Product Lifecycle Management (PLM), a plethora definition of DTs emerged: an integrated multidisciplinary simulation of a physical system, a virtual model of a physical asset, or a reflection of the life of a product using sensors [6]. Which is why DTs are considered a versatile tool, applicable to various fields [6]. Later, Grieves and Vickers (2017) refined the definition to highlight its role in addressing unpredictable emergent behaviors in complex systems. Ultimately, DTs facilitate the integration of physical and digital systems, enhancing operational efficiency, predictive analysis, proactive decision making and system resilience (Kritzinger et al., 2018).

Several papers discuss the concept of a digital twin as a representation or replica of a physical entity, but the idea of a digital twin being an "exact" copy is generally not supported across all the sources. Some references do however suggest that a digital twin should be a high-fidelity representation of the physical twin, aiming for a close and detailed virtual model. There are many misconceptions about Digital Twins. Some sources note that there is a tendency to believe that a DT includes an exact 3D model, but that is not always the case (Boyes & Watson, 2022; Fuller et al., 2020). The reality is that creating a completely exact copy may not be feasible or practical, due to factors like network speeds, computational power, and the limitations of data acquisition. There are trade-offs to be made between accuracy and feasibility (Jones et al., 2020). The actual implementation often uses a subset of parameters rather than capturing every aspect.

In this context, high-fidelity means the digital model is as accurate and detailed as necessary for the intended use case, not necessarily a 1:1 copy (Fuller et al., 2020; Javaid et al., 2023; M. Liu et al., 2021; Thelen et al., 2022). The degree of accuracy depends on the application and engineering problem it seeks to solve. Since it is difficult for the digital space to mirror all aspects of the physical space, a digital twin is always constructed for specific aspect(s) relevant to the engineering problem the digital twin is used to solve, and these aspect(s) need to be specified before the construction of the digital twin (Thelen et al., 2022).

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several papers reviewed herein build simulations and call them DT, but it is unclear if these simulations have the full capabilities usually associated with DT. Simulation and DT are distinct technologies with unique benefits that can provide important insights to a problem; therefore, they should be classified accordingly, and it is crucial to clarify their differences to prevent misunderstandings.

Traditional simulation and DT models share the same ability to replicate a physical system in a virtual environment, but they are not the same [14]. The use of simulation combined with a DT is very common, which creates an immense misconception about classifying a simulation model as a DT and vice versa [16]. Several organizations use the term ‘Digital Twin’ synonymously to a simulation model and several software and consulting companies are creating and selling simulation software claiming it is a DT [17]. Besides having the capabilities to model and simulate the physical system in a virtual environment, a DT presents continuous bilateral communication, it measures the changes in the physical system by sensors, and predictions are constantly being shared with the physical system for real-time decision making [18].

***A Requirements Driven Digital Twin Framework: Specification and Opportunities:***

To date, no consensus has been reached on a DT definition in manufacturing. The DT label is often applied to any capa- bility that replicates some aspect of a system, e.g., simulation of anything in manufacturing. It is the opinion of the authors that most DT definitions either implicitly or explicitly state the following properties of a DT:

* It is some level of replica of a real thing.
* It exists in the cyber world, i.e., it is a software entity.
* It has a purpose of impacting an aspect of the environment in which its real counterpart exists, in a positive way, usually by serving one or more DT clients. This purpose can be broad or very refined and the impact mechanism can vary widely.
* It uses models to achieve its purpose.
* It incorporates some level of subject-matter-expertise (SME, which will also be used to refer to ‘‘subject- matter-expert’’ in this paper) in the solution. This could be as simple as defining the problem, or as complex as being an integral part of the model solution. Some efforts illustrate that the combination of SME and data provides more effective, robust and usable solutions in many manufacturing domains, than purely data-driven solutions [6], [9].
* It uses data to maintain some type of synchronization with its real counterpart. In most definitions, this data is collected in an operation environment.

In summary we can thus make the following statements on the state-of-the-art and trends for DTs in manufacturing:

* Many manufacturing industries are already successfully employing DT components, though these components have not been referred to as DTs until very recently.
* Most of the DTs in use in factory operation are dedicated DTs, each with a specific purpose such as predicting remaining useful life or optimizing product quality. A specific class or type of DT commonly has a specific objective (e.g., process optimization), pre-definition of operation environment (e.g., equipment, process, and other context), and defined methods or guidelines for development and deployment.
* DTs such as general equipment and software simulators are also available, with their purpose less directed (i.e., the capability being improved is not as succinctly specified, is not directly considered in the design of the simulator, or the capability is one of many to which the simulator can be configured to address), and capability boundaries usually not as well-defined [48]. These DTs are generally not used during actual manufacturing (e.g., they might be used for off-line analysis or planning); however, DTs that are more dedicated to a specific purpose, as described above, might be built from specific configurations using the general simulators and then applied during manufacturing.
* The quality, throughput and cost pressures in some industries have led to DT advancements and a requirement that DTs be an integral part of factory solutions in many areas.
* There is often little coordination of DT technology between the DT application areas. As an example, model-based process control (MBPC) and model-based PdM literature bases rarely overlap.
* Manufacturing is beginning to explore and benefit from abstracting and combining DT solutions [49], [50].

The definition considered for the rest of this paper is: “A Digital Twin is a virtual representation of a physical entity or system, synchronized in real-time with its physical counterpart and enabling continuous data flow and interaction. This connection allows for simulation, analysis, and informed decision-making throughout the lifecycle of the physical entity (Grieves & Vickers, 2017; Tao & Zhang, 2017)”.

Fuller et al. (2020) classify DTs into three primary types as a categorical framework for understanding their development:

1. **Digital Models:** Representations of physical entities with no links to the physical counterpart.
2. **Digital Shadows:** with one-way automatic connection from the physical to the virtual twin, which allows it to reflect changes in physical entities in real-time.
3. **Digital Twins:** Establish a bi-directional automatic data exchange between the physical and digital components.

***Which arguably begs the question that has never been explicitly tackled in the literature: How to classify the virtually twinned systems with one-way automatic connection from the virtual to the physical twin? (a control system? a human machine interface, a cyper-physical system (to an extent)?)***

***DT characteristics:***

While the distinction made by Fuller et al. (2020) clearly sums up the essential pre-requisites to be a DT, other requirements can be identified in the literature that go further in dept into a rather functional definition of DTs. Several other digital twin frameworks can be found in the literature that give a description of DT components. **For instance … (talk about the 3 dimentional and 5 dimensional and other models).** To curate a concrete checklist of what a DT is required to be, a review of conceptual models and state of the art DT applications, definitions, requirements, characteristics and features was conducted. The following list sums up the DT characteristics:

**1) Physical Entity:** The real-world object, system, or process that the digital twin represents (Jones et al., 2020). This could be a single device or an extensive system. To a certain extent elements of the physical environment surrounding the physical system should also be included in the scope of the DT modeling framework.

**2) Virtual copy:** **:** A digital representation or copy of the physical entity, describing its properties in multiple dimensions (Jones et al., 2020). It can include detailed information about its design, manufacturing, and operational characteristics. The digital counterpart is embedded in a virtual environment that allows it access and interoperability with other digital systems such as cloud technology, information systems and other DTs.

**User interface** is an essential component of a digital twin system, allowing users to interact with the DT, access its information, view its status, run simulations, or change its configuration. A user interface typically includes a visual display of the DT, such as a 3D model or dashboard, and interaction tools like buttons, sliders, and other controls [42]. A user interface can also run simulations or change the DT’s configuration by adjusting parameters or testing different scenarios. This helps users understand how the physical twin would behave in other conditions and identify potential issues or opportunities for improvement.

**3) Real-Time Data synchronization (Physical-to-Virtual Connection):** The ability to seamlessly synchronize data with the real-world counterpart, allowing for continuous monitoring and simulation [52]. DTs must leverage real-time data to accurately represent the state of their physical counterparts [5, 7]. The integration of robust data sources is critical to ensuring high-fidelity representation [7]. Real-time data also facilitates the detection of behavioral anomalies, contributing to proactive system monitoring [8].

**Data Storage and Processing:** Data is the backbone of digital twins. Some experts have expanded the original digital twin concept to include data and services [46,83]. All data that is exchanged must be stored in a data repository accessible to DT, which results in a significant storage demand [72]. This data can include historical data, metadata, and derived data [42]. To manage high-dimensional data effectively, digital twins employ advanced techniques for handling, analyzing, and decoding high-dimensional data and algorithms for merging multiple data sources to produce more accurate and valu- able information [43,86,87].

**Integration:** A digital twin must integrate data from multiple sources and hierarchical levels, including component-level data, physical attributes and process dynamics [5, 7, 8]. If applicable, ensuring interoperability and communication across different systems and domains, be it IoT, information systems, cloud or even open access data for some cases, is also a fundamental requirement [9]. Network devices that ensure seamless connectivity and data exchange, either directly or via the cloud should also be considered if possible.

**4) Feedback and Control (Virtual-to-Physical Feedback):** A DT must facilitate bidirectional communication between the virtual model and the physical entity. This interaction includes both the transmission of real-time data from the physical system to the digital twin and the capability to send control commands back to the physical system [5]. Such bidirectionality is essential for real-time system regulation and optimization [3]. **(talk about systems with humans in the loop)**

**5) Fidelity:** The virtual replica must maintain high accuracy to its physical counterpart [5, 7]. Fidelity in this context refers to the precision and accuracy with which a DT replicates the characteristics, behaviors, and states of the physical system. A high-fidelity DT can effectively simulate real-world behavior; however, excessive fidelity may lead to unnecessary computational costs and complexity [10]. For instance, a DT focused on optimizing an industrial plant’s energy consumption may only require electrical consumption data rather than a comprehensive representation of all operational variables [11]. Fidelity is the ability of the digital system to produce the same results as the physical system when given the same stimuli and input.

**6) Autonomy:** Digital twins should be capable of self-monitoring, self-diagnosis, self-optimization, and adaptive behavior based on real-world environmental changes [6]. Enhanced autonomy is a crucial feature for future applications, enabling more efficient and intelligent decision-making [5]. **(for now this doesn’t talk about its autonomy to communicate and make changes to the real world)**

**7) Continuous Evolution:** DTs must exhibit continuous evolution, adapting to changes in their physical environment [6, 4]. They should be capable of learning and improving over time through iterative refinement and data-driven insights [5].

**8) Multimodal Modeling:** DTs should integrate multimodal data, encompassing physical models, behavioral models, operational rules, and data models [10] when relevant. This approach involves combining physics-based models that define physical properties and behaviors with process data that capture system performance metrics. Additionally, behavioral modeling enhances the DT’s ability to simulate system responses to various stimuli, while rule-based models formalize operational constraints and procedures and over different time periods with various levels of granularity, particularly for trend analysis [34].

**Predictive Capabilities:** They can forecast future states and emergency events by using predictive algorithms, which allows stakeholders to be proactive rather than reactive. This helps in risk mitigation and better planning.

**Data-Driven Decision Making:** The data collected and processed by digital twins enables informed and optimized decision-making. The ability to analyze data helps in identifying patterns and trends that can lead to better management of projects.

**Statistical and AI algorithms** can analyze data and provide in- sights, predictions, and recommendations. Digital twins also depend on AI to adapt and improve as new data is generated. To reduce the cost of storage and computation, the preferred AI techniques should be able to minimize data dimensionality while still preserving the most valuable data for the DT [44,88]. DTs use statistical applications, pattern recognition, and unsupervised/supervised learning to process and analyze data from the physical twin and its surrounding environment. It enables the detection of changes and the identification of patterns and trends [42].

**9) Adaptability:** DTs must be able to adapt to environmental changes while maintaining their performance for effective utilization [5]. Adaptability is a crucial characteristic that ensures the relevance of DTs in dynamic and evolving environments. An adaptable DT should be capable of modifying its behavior in response to unforeseen situations and achieving its objectives [12]. This adaptability may involve updating models, adjusting control parameters, or reconfiguring the physical system. To achieve this, a DT must integrate new data, update its models, and refine its predictions in real time [13]. Machine learning techniques also enable DTs to adjust system behavior with minimal human supervision [12]. Implementing self-adaptive models that can dynamically modify their parameters in response to evolving conditions and objectives ensures that the DT remains relevant throughout its lifecycle [12, 14].

**10) Context Awareness:** The ability of the DT to accurately represent the physical entity within a specific application context, considering the source of data and environment [23]. A DT must maintain awareness of its operational context to enhance adaptability [4]. Context awareness enables a DT to interpret data meaningfully by considering its physical and logical environment. This capability extends beyond mere data perception, requiring the DT to establish relationships between collected data, user preferences, and environmental factors. Context awareness is crucial for autonomous decision-making and for ensuring seamless cooperation among multiple DTs, particularly in complex environments such as smart manufacturing systems.

**11) Security and access control components** are essential to ensure the integrity and confidentiality of the data and the design [89, 90]. Security and access controls ensure the data and system integrity and confidentiality. Some examples of security and access control components in the DT system include authentication and authorization elements, intrusion detection and prevention components, and data leakage prevention components [91–93].

**12) cognition:**

The design and implementation of digital twins are highly application- and equipment-specific, with no universally standardized development methodology. The field requires a structured taxonomy to better classify DT applications. Key DT requirements revolve around real-time data utilization, integration capacity, and fidelity [7, 8, 9]. While researchers primarily focus on the technological requirements of DTs, industry stakeholders prioritize value-driven properties that enhance operational efficiency [10]. The applicability of DTs remains broad and varies based on lifecycle stage and industrial sector, highlighting the need for cross-disciplinary collaboration in their development.

**Digital Twin Evaluation Framework**

The evaluation framework questionnaire has a double purpose: allow the respondent to assess if their system adheres to research’s definition of digital twins and identify the level of digital twins they are at and secondly it will be applied to WMS to see how far off digital twins the technology is. To do so a number of WMS specialists are contacted to answer the questionnaire.

***Instructions:***This questionnaire is designed to help you assess whether your system qualifies as a Digital Twin (DT) according to research definitions. For each statement, please rate the extent to which your system meets the criterion using the following scale:

* ***1:*** *Not at all*
* ***2:*** *To a small extent*
* ***3:*** *Moderately*
* ***4:*** *To a great extent*
* ***5:*** *Fully/Completely*

*Note: Throughout this questionnaire, the term “system” refers to the virtual model, information system, or simulation under evaluation.*

**1. Core Digital Twin Characteristics**

Digital Twins are virtual representations of physical entities, enabling seamless bi-directional data exchange for real-time monitoring, simulation, and decision-making (Grieves & Vickers, 2017; Tao & Zhang, 2017). The core DT components are the physical entity, the virtual copy and the data transfer linking them to one another.

**1.1 Physical-Virtual Representation**

**Physical Entity:**

* How clearly is the real-world physical entity defined?
* How clearly are the entity’s boundaries and hierarchical levels (e.g., unit, system, system of systems) specified regarding the purpose of the system?
* How well are physical and environmental parameters (e.g., temperature, pressure, operational context) influencing the physical system identified?

**Virtual Entity (system subject to evaluation):**

* How accurately does the virtual system represent the physical entity within its specific application context?
* Is the representation granular enough to capture detailed interactions and changes relevant to the system’s main objective (geometry, behavior, and functional rules)?
* Does the system include an intuitive user interface that for interaction, access, analysis or experiment run?
* How easily can someone, other than the creator, use the system?

**2. Connectivity and Synchronization**

A fundamental feature of DTs is their ability to maintain dynamic, bi-directional connections between physical and virtual entities. This involves ensuring synchronization through real-time or near-real-time data flows to support operational and strategic objectives (Hribernik et al., 2021; Liu et al., 2024) followed by the ability of the system to react and interact with the physical entity when needed (Whitin its application scope). **[References !!!!]**.

**2.1 Bidirectional Data Flow**

**Physical-to-Virtual Connection:**

* How automated is the process of transmitting data from the physical entity to the virtual system?
* How often is the data transmitted from the physical to the virtual system? *(1- being never and 5 - real time)*
* How well is the system integrated with other relevant systems (e.g., within a cloud environment)?
* Are the system’s parameters regularly updated based on real-world data?

**Virtual-to-Physical Feedback:**

* Is there a mechanism for real-time decision-making that optimizes physical operations?
* How seamlessly, within the scope of the system application, can it initiate interaction or actions in the physical entity? *(1 being no reaction possible, 5 being sending control commands or notifications to humans in the loop)*

**2.2 Synchronization**

**State Synchronization:**

* Is the method for connecting the physical and virtual components (e.g., sensors, IoT devices) clearly defined?
* How frequently does the system synchronize data? (1 = Never; 2= Startup or on demand; 3= Everyday; 4= periodically; 5 = Real-time)
* How well does the synchronization interval match the requirements for decision-making?

**Historical and Predictive States:**

* How effectively does the system reflect historical, current, and predicted states?
* Is predictive synchronization integrated with models (AI) to anticipate operational behavior offline?

**3. Modeling, simulation and Decision Support**

Digital Twins enable analytical, predictive and prescriptive capabilities through computational engines, providing actionable insights and optimization strategies. These capabilities align with transitioning decision-making from reactive to proactive processes (Wagg et al., 2020; Ivanov & Dolgui, 2021).

**3.1 Simulation Capabilities**

**Modeling and What-If Scenarios:**

* Does the system have a computational engine to support simulation and decision-making?
* Can the system evaluate "what-if" scenarios for varying operational settings?

**Optimization:**

* Are optimization algorithms or methods applied to improve performance metrics (e.g., energy, logistics, costs, sustainability)?
* How effectively can the system analyze trade-offs (e.g., sustainability vs. cost efficiency)?
* Does the system provide actionable insights to humans in the loop?

**4. Data Management and Integration**

DTs depend on robust data collection, integration, and processing frameworks to ensure seamless real-time operations. This includes IoT devices, cloud/edge computing, and compatibility with enterprise systems.

**4.1 Data Collection and Processing**

**Data Fusion and Integration:**

* Does the system have access to historical data?
* How well is the system integrated with physical environment (e.g., ERP, MES, PLM, WMS, IoT, sensors)?
* To what extent are multiple data sources (sensor data, static data, predictive outputs) fused for comprehensive insights?
* How well is data heterogeneity managed (handling different formats, resolutions, or sources)?
* How effectively does the system integrate multi-modal data (structured vs. unstructured, historical vs. real-time)?

**5. Learning, Adaptability and Autonomy**

A mature DT leverages AI and machine learning to self-improve, recognize context changes, and adapt its models autonomously. This adaptability ensures scalability and relevance throughout its lifecycle (Hribernik et al., 2021; Liu et al., 2024).

**5.1 Context Awareness**

**Environmental Awareness:**

* How well can the system recognize changes in its environment?
* How well does the system incorporate component interactions, disruptions, and uncertainties into its models?

**5.2 Learning Capabilities**

**AI and Machine Learning:**

* How advanced is the system’s self-learning capability? *(1 = No intelligence, 5 = Fully autonomous learning)*
* To what extent does AI/ML contribute to predicting, analyzing, and optimizing performance?
* How capable is the system of learning from past experiences and adapting to new situations?

**5.3 Adaptability and Evolution**

**Dynamic Adjustments:**

* How scalable is the system in integrating new equipment, functionalities, or processes? *(Not scalable | Poorly scalable | Moderate scalability | Highly scalable | Fully dynamic integration)*

**Lifecycle Management:**

* To what extent is the system applicable throughout its physical counterpart’s lifecycle?

**Cognitive Capabilities:**

* To what extent can the system reason and make decisions autonomously?
* How interpretable and explainable are the DT’s decisions?

**5.4 Autonomy**

**Autonomous Actions:**

* How capable is the system of updating itself (e.g., its logic and parameters) without external intervention?
* How effectively does the system communicate with external systems?
* How well can the system independently make and execute decisions within its predefined application scope?

*Find these questions elsewhere and link them as well to this section in the evaluation: Can the system interact with other systems and adapt to its environment? Does the digital twin possess context awareness (system state, operational environment, objectives)? Can the system modify control parameters of the physical system based on analysis?)*

**6. Fidelity and Validation**

DTs aim for high-fidelity representations while balancing computational efficiency. Validation ensures their trustworthiness and alignment with physical behaviors, critical for stakeholder confidence (Wagg et al., 2020; Melesse et al., 2021).

**6.1 Model Fidelity**

**Abstraction Level:**

* How appropriate is the model fidelity for achieving the system’s goals?
* To what extent are uncertainties or tolerances in the virtual model quantified and managed? *(1= Not considered; 5= Fully managed and transparent uncertainty modeling)*

**Trust and Confidence:**

* How well does the results of the system’s computational engine correspond to the actual behavior of the physical system (given the same stimuli)?
* How reproductible is the system’s behavior (given the same inputs)?

**6.2 Verification and Feedback**

**Model Validation:**

* How comprehensively rigorous is the system’s verification process (e.g., testing, sensitivity analysis, real-world comparisons)?

**Continuous Improvement:**

* How effectively does the system use real-world outcomes to refine its models?
* How frequently does the system incorporate new data to update its models?

**7. Digital Twin Services**

The functional utility of DTs is measured by their service capabilities, such as real-time monitoring, predictive maintenance, and operational optimization, aimed at enhancing the physical entity's performance and resilience (Jones et al., 2020).

**Monitoring and Real-Time Feedback:**

* How effectively does the system monitor key metrics (e.g., energy consumption, performance, errors) in real-time?
* How portable is the system across various devices and platforms?

**Failure Analysis, Prediction and Optimisation:**

* How capable is the system of forecasting future states and emergency events?
* Does the system enable predictive analytics?
* Does the system provide prescriptive analytics?

**8. Technological Readiness**

The deployment of DTs depends on the integration of advanced technologies such as IoT, cloud computing, AI/ML, and ensuring cybersecurity. Scalability and compliance with privacy standards are also critical considerations (VanDerHorn, 2021).

**Enabling Technologies:**

* To what extent are advanced technologies (e.g., IoT, cloud/edge computing, AI/ML, big data, 5G) integrated into the system (regarding its application and scope)?
* Does the platform allow domain experts to operate the system without needing deep technical expertise?

**Security and Data Privacy:**

* Does the system reliably prevent unauthorized access to data?
* How effectively are cybersecurity risks and data privacy concerns addressed?
* How robust are the protective measures in place to guarantee data privacy?

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**Technologies usually mistaken for DTs:**

* Digital model (off line Simulation)
* Digital Shadows
* Cyber-physical System
* 3D Models & CAD
* Digital Thread: A digital thread covers the development cycle of a product and is used for making predictions and decisions [58]. The digital thread also has a role in creating sustainable environments, whereas the DT processes the data sent by the physical entity [58].
* Building Information Modeling (BIM)
* Information Systems (WMS, ERP, SAP …)
* Internet des objets (IoT)
* SCADA (Supervisory Control and Data Acquisition)
* Extended reality

**Différence entre jumeau numérique et système cyber-physique (CPS) :** Le document distingue clairement un jumeau numérique d'un CPS. Le CPS est un système holistique où les éléments numériques et physiques sont intrinsèquement liés et nécessaires à son fonctionnement [24]. Le jumeau numérique, quant à lui, est un modèle virtuel interconnecté qui représente l'objet physique, mais n'est pas essentiel au fonctionnement de ce dernier [25]. L'entité physique peut fonctionner de manière autonome sans son jumeau numérique [24].

**Digital Twin Levels, and maturity models:**

Several sources emphasize that a maturity model should serve as a framework to evaluate the development stage of a digital twin, guide its progression, and provide a common understanding among stakeholders (Duan & Tian, 2020; Hu et al., 2023; Y. Liu et al., 2024). Maturity models are stratified, describing the evolution of an entity through distinct levels. They should provide a clear and unified framework for communication among stakeholders.

Liu et al.: This study introduces a Digital Twin Maturity Model (DTMM) divided into five levels. This model is aimed at assisting project decision-makers and public policy planners to better understand digital twins and facilitate their deployment more effectively. It integrates the objectives and tasks of each level with the associated requirements and technologies. The DTMM enables a comprehensive assessment of the current level of capability and development of digital twins, providing guidance for project managers. This model offers an overview of digital twin development, with levels serving as a roadmap for improvement, helping to evaluate how well a digital twin is developed and to identify potential enhancements.

Hu et al.: This source develops a maturity model specifically for high-end equipment. This model combines both qualitative and quantitative analyses. The qualitative analysis is based on 3 dimensions and 27 rubrics, while the quantitative analysis uses the Analytic Hierarchy Process (AHP) and the matter-element extension method. The model proposes six maturity levels for each rubric, facilitating the evaluation and improvement of digital twins. This model is therefore intended for a rigorous assessment and targeted improvement of digital twins, particularly for complex applications where precision is paramount.

*Maturity Levels of Digital Twins:*

Level 0: Digital Model: A static representation of physical and geometric properties, based on offline data. The digital model is closest to a simulation, allowing for basic calculations and one-shot decision making. However, it requires a lot of maintenance since it doesn’t mirror, nor evolve with the physical entity.

Level 1: Digital Shadow/Connected Twin: A digital model connected with a unidirectional data flow from the physical system to the model, but without control or feedback.

Level 2: Digital Twin/Interactive Twin: Bidirectional data exchange, enabling dynamic interactions between the physical and digital systems. It allows simulation and optimization and can have basic control or contact with the physical counterpart.

Level 3: Predictive Twin: Advanced simulation and prediction capabilities, using data analysis and algorithms to anticipate future states and potential problems. This level allows monitoring, analysis, and prediction of the physical twin's future behavior.

Level 4: Autonomous Twin: The digital twin can act autonomously, using AI to make decisions and adapt automatically. This level incorporates self-regulation, self-monitoring, and self-diagnosis capabilities et free willed control and decision making.

Level 5: Co-Intelligence/Orchestrated Twin Ecosystem: Multiple digital twins interact and collaborate to form higher-level digital twins, forming a fully integrated and scalable ecosystem.

Level 6: cognitive digital twin: Distinguished by its integration of cognitive abilities, enabling it to perform autonomous actions. It can learn, adapt, and make decisions proactively, while also ensuring comprehensive lifecycle management with advanced artificial intelligence and learning capabilities. This placement is illustrated in several models, including in the model by Liu et al., a cognitive digital twin surpasses the standard digital twin and aligns with the cognitive or federated twin levels, where it analyzes and makes decisions using learning and interconnects several digital twins to create a complex ecosystem. The Jan-Frederik model also indicates that a cognitive digital twin is at the highest level, which includes complete life-cycle management with autonomous learning and decision-making.

**Digital Twin Maturity Levels ("A review of digital twin capabilities, technologies, and applications based on the maturity model"):** This paper introduces a five-level maturity model (DTMM) for digital twins:

* **Level 1:** Basic digital representation of a physical entity.
* **Level 2:** Includes data connectivity with the physical entity.
* **Level 3:** High-fidelity virtual models with two-way communication.
* **Level 4:** Automation and integration of various functions.
* **Level 5:** Self-optimization and autonomous operation.

6 maturity levels of DT, including the Basic Level (Level 1), the Connection Level (Level 2), the Integration Level (Level 3), the Perception Level (Level 4), the Interaction Level (Level 5), and the Autonomy Level (Level 6).

Une image contenant texte, capture d’écran, Site web, Page web

Le contenu généré par l’IA peut être incorrect.

**Digital Twin Sophistication Levels ("** **Digital twins: State-of-the-art and future directions for modelling and simulation in engineering dynamics applications"):** This paper defines five levels of sophistication:

* **Pre-Digital Twin:** A system capable of being a digital twin, but lacking essential elements [55].
* **Simulation Digital Twin:** A digital twin with simulation capabilities [55]. The other levels are not defined in this excerpt.
* **Digital Twin 8-dimension model** ("read 44433.pdf"): This model provides each layered model of 8 Digital Twin dimensions. Its technical levels can be considered from a maturity perspective [15].
* **Digital Shadow** ("read kinda.pdf"): Unlike a digital twin with bi-directional data flow, a digital shadow primarily focuses on representing the state of a physical object in the digital realm [52]. It lacks the interactivity and autonomous evolution of a digital twin and mainly emphasizes gathering and analyzing historical data [52].

**5. Unified Maturity Model for Digital Twins**

Creating a single unified maturity model based on all the sources is challenging because they offer different perspectives. However, I can combine elements from several models to create a comprehensive model:

**Unified Digital Twin Maturity Model**

* **Level 0: Pre-Digital Twin**
* Description: A system that has the potential to be a digital twin but lacks key functionalities and characteristics.
* Characteristics: May have some digital data related to the physical entity but lacks real-time or bi-directional data exchange [55].
* **Level 1: Basic Digital Representation**
* Description: A basic digital model or representation of a physical entity.
* Characteristics: May have a static digital model, but no real-time connection or bi-directional data flow. Focus on data collection and monitoring without control [10, 20].
* **Level 2: Connected Digital Twin**
* Description: A digital twin with data connectivity to the physical entity.
* Characteristics: Includes data connectivity for monitoring and visualization, and may have basic simulation capabilities. Data is being collected but there are limited autonomous or learning functions [20, 40, 41].
* **Level 3: Interactive Digital Twin**
* Description: A high-fidelity virtual model with bi-directional communication, and feedback control.
* Characteristics: Enables two-way data exchange, more accurate virtual model, real-time monitoring, simulation and interaction. Includes data processing, analytics and decision-making support [20, 41].
* **Level 4: Autonomous Digital Twin**
* Description: Includes automated processes and integration of various functions, enabling greater level of self-regulation, self-adaptation, and prediction.
* Characteristics: High level of interaction and optimization and autonomous operation. May include AI/ML capabilities for learning and adaptation with a focus on prediction and optimization [36, 61].
* **Level 5: Adaptive and Context-Aware Digital Twin**
* Description: A digital twin that is self-optimizing, autonomous and context-aware, with a high degree of adaptability, autonomy and the capacity to function within diverse contexts.
* Characteristics: Real-time optimization, self-diagnosis and fully autonomous operations with the ability to manage uncertainty, model validation and adaptability to new conditions. Full closed loop communication between physical and virtual entities [36, 48].

**Disclaimers:**

This survey is mainly used to evaluate if the respondent is modeling a digital twin. This relates mainly to the standard of the art qualification and requirements of a digital twin definition but doesn’t necessarily regard the finesse of said system. Questions like the following examples aren’t considered as they are too practical:

* Quel type de méthodologie de modélisation est utilisé (choisir toutes les options applicables) ? Modèles basés sur la physique - Modèles axés sur les données -Modèles d'apprentissage automatique …
* Le modèle virtuel est-il une abstraction mathématique ou une simulation qui vise à simuler ou à reproduire le comportement de son homologue physique ?
* Les données sont-elles traitées pour éliminer le bruit, les valeurs aberrantes ou les informations inutiles ?
* Le système utilise-t-il l'analyse de données pour fournir des informations utiles sur le système physique ?
* Quels sont les objectifs de l'utilisation du système de JN ? (Veuillez choisir toutes les options applicables)
* Le système utilise-t-il des systèmes cyber-physiques (SCP), l'Internet des objets (IdO) ou l'apprentissage automatique (AA)/l'intelligence artificielle (IA) ?

However, the references that have insinuated these questions are used in training the LLM for further and pointed assistance to the respondent when using the gpt.

``

Once the questionnaire is completed, the Streamlit application for Digital Twin maturity assessment and recommendations should:

* Provide immediate feedback based on the scores and comments.
* Generate actionable recommendations for improvement.
* Allow ongoing user queries.

**Training and Knowledge Base**: Use the provided PDFs to train your GPT model or enhance its knowledge using embeddings or fine-tuning. This involves:

* Extracting relevant knowledge about Digital Twins, their maturity, AI integration, and warehouse management.
* Preparing a dataset from the PDF, ensuring key concepts and case studies are easily accessible.

**Survey Participant hunt (Whitney):**

**Evaluation Method (post survey)**

Fuzzy logic, pioneered by Zadeh in 1965, provides a robust mathematical framework for handling imprecise or ambiguous data, which is often encountered in real-world scenarios. In the context of evaluating Digital Twins (DTs), fuzzy logic enables the quantification of qualitative judgments and the integration of subjective assessments into a structured evaluation process. By defining fuzzy sets and rules, evaluators can analyze the performance of DTs across various dimensions, even when precise measurements or binary decisions are not feasible.

Digital Twins, being complex systems with dynamic interactions between physical and virtual entities, require an evaluation methodology that can capture nuances like partial performance, intermediate system states, and varying degrees of achievement. Fuzzy logic facilitates this by:

* Allowing **linguistic variables** (e.g., Low, Medium, High) to replace rigid numeric inputs.
* Utilizing **membership functions** to assess the degree to which a particular input belongs to a category.
* Supporting **fuzzy inference systems (FIS)** that aggregate and interpret diverse input data to generate actionable insights.

This approach aligns with modern research trends in evaluating cyber-physical systems and predictive modeling, as it provides a scalable, adaptive, and interpretable methodology.

**Methodology for Fuzzy Logic Implementation in DT Evaluation:**

1. **Definition of Linguistic Variables and Membership Functions:**
   * Define key evaluation criteria (e.g., quality, performance, accuracy) as linguistic variables.
   * Use membership functions (e.g., triangular or trapezoidal) to represent degrees of membership for each variable.
   * Example:
     + **Quality**: Low (0–5), Medium (3–7), High (5–10).
     + **Performance**: Low (0–5), Medium (3–7), High (5–10).
2. **Rule-Based Fuzzy Inference System (FIS):**
   * Construct logical rules that define relationships between inputs and outputs.
   * Example rules:
     + If **Quality** is Low or **Performance** is Low, then the **Score** is Poor.
     + If **Quality** is Medium and **Performance** is Medium, then the **Score** is Average.
     + If **Quality** is High and **Performance** is High, then the **Score** is Excellent.
3. **Fuzzy Aggregation and Defuzzification:**
   * Combine fuzzy input variables using logical operations (e.g., AND, OR).
   * Aggregate the results into a crisp output (e.g., overall score) using defuzzification methods such as centroid or mean of maxima.
4. **Integration into the Evaluation Framework:**
   * Replace rigid scoring methods with fuzzy linguistic inputs.
   * Use sliders or other interactive widgets in Streamlit to collect evaluator inputs in linguistic terms.
   * Process these inputs using the fuzzy inference system to generate scores and insights.
5. **Advantages of Fuzzy Logic for DT Evaluation:**
   * Handles ambiguity and partial truths effectively.
   * Reflects expert knowledge and domain-specific heuristics in a structured way.
   * Provides interpretable results that align with human reasoning.

This methodology, supported by a fuzzy logic engine, ensures that the evaluation framework is both rigorous and flexible, accommodating the complex and dynamic nature of Digital Twin systems. Let me know if you'd like me to refine or extend this methodology or implement additional elements into the framework!

**WMS :**

The advancements of Industry 4.0, particularly through the integration of cyber-physical systems like Digital Twins (DT), have unlocked new possibilities for sustainable warehousing (Oloruntobi et al., 2023; Nantee & Sureeyatanapas, 2021). DT technology enables the creation of real-time virtual replicas of physical warehouse environments, allowing precise tracking, simulation, and optimization of resource use and emissions across functional areas such as sorting, picking, and storage (Drissi Elbouzidi et al., 2023; Perotti & Colicchia, 2023). This aligns with Industry 5.0’s focus on sustainability and human-centric processes, enhancing both environmental goals and worker well-being (Möller et al., 2022; Grosse, 2024).

DTs bridge the operational efficiency of Industry 4.0 with the ethical imperatives of Industry 5.0 by integrating with data from WMS to deliver actionable insights. Through predictive analytics, real-time monitoring, and scenario modeling, DTs optimize warehouse operations and facilitate sustainable reporting while aligning them with sustainability objectives.

SWM faces significant challenges due to the lack of standardized sustainability metrics and comprehensive measurement frameworks (Rüdiger, 2016). Many studies fail to integrate the environmental, social, and economic pillars of sustainability cohesively, leaving critical gaps in their applicability (Ahmad et al., 2018). The development of Sustainable Warehouse Management Systems (SWMS) remains hindered by the complexity of addressing diverse sustainability factors (Torabizadeh et al., 2019). While WMS are widely used for inventory and operational efficiency, their potential to promote sustainability remains underdeveloped (Happonen & Minashkina, 2021). Advanced functionalities, such as tracking energy consumption, waste generation, and carbon emissions, are largely absent. Though a WMS can optimize processes like material handling and route planning to reduce energy use, explicit strategies for integrating sustainability objectives are lacking (Torabizadeh et al., 2020; Minashkina & Happonen, 2023). Additionally, integrating technologies like IoT and cyber physical systems with WMS shows promise but is often cost-prohibitive and hampered by outdated systems and limited interoperability (Minashkina, 2024). According to the 2024 Warehouse/DC Operations Survey, 93% of respondents use WMS, but 45% report outdated equipment and 44% still rely on paper-based picking, limiting the capacity of a WMS to advance sustainability (Michele, 2024).

Despite these advances, the adoption of DTs for green warehousing is still in its nascent stages. Many companies are hesitant to invest in the necessary infrastructure due to high initial costs and the complexity of implementation (Maheshwari et al., 2023). However, as regulatory pressures increase and sustainability becomes a competitive advantage, the integration of DTs with WMS offers a viable pathway for achieving both operational efficiency and environmental stewardship (Kamble et al., 2022). Future research should focus on developing standardized sustainability indicators for DT-enabled warehousing, addressing gaps in data availability, and exploring the socio-economic impacts of these technologies (Drissi Elbouzidi et al., 2023).

Step 3- Configuring the DT: activity parameters are configured to be calculated for each resource in the DT. This is where the DT surpasses traditional information systems like WMS, as it enables tracking information that is rarely available in real-life without advanced instrumentation. For instance, forklift operating time can be directly monitored through the DT to calculate their direct process emissions, which is typically challenging or impossible in physical warehouses without specialized tools. Most conventional tools and methods rely on contractual data, such as estimated operating hours provided at the time of equipment acquisition. However, the DT allows for calculating impacts based on actual field data and simulated scenarios, offering a higher level of precision for dynamic, resource-specific environmental assessments, bridging critical data gaps often encountered in traditional systems.

Without DT integration, reliance on WMS limits operational insights, as shown in Table 3, highlighting the difference between the data available.



The DT offers a more detailed dataset, accurately modeling real-life processes and capturing data that a WMS cannot, such as auxiliary movement of forklifts. These activities can nearly double operational time, which WMS cannot fully track as it only records time intervals between pallet scans to estimate transportation time.

* Beaucoup de question sur le rôle d’un WMS sur l’étude elle-même. Comme mentionner plusieurs fois. Dans un entrepôt, surtout un entrepôt manuel, les sources de données d’un jumeau numérique au finale se résume au WMS. Celui la indirectement rempli déjà pas mal de critères concernant les caractéristique d’un JN et donc la question se pose : Comment basculer du WMS actuel, « statique » vers le WMS de demain qui est essentially un JN ? est ce que le JN est la suite du WMS ? comment intégrer un JN à un WMS peut-être et pas le contraire ?
  + ***WMS 🡪 JN : transition ou rupture ?*** (et voir avec les modèles économique ? whatever that means)
  + ***Serait le WMS au bout d’un moment capable d’absorber le JN ?***

1. Consider emphasizing the practical challenges of integrating DT technologies with existing WMS in manual versus automated warehouses.
2. Address scalability and interoperability challenges when considering a hybrid WMS-DT system.
3. Discuss sustainability implications, as DTs could optimize resources better than current WMS.

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