***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-dimensional framework and 5D 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:

**Physical System:** 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.

**Digital System:** 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.

**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.

**Bidirectionality 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)**

**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.

**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)**

**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].

**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].

**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].

**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.

**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].

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**

*Throughout this entire questionnaire, the word “system” refers to the virtual model, IS or simulation subject to the evaluation to deem if it is indeed a DT according to research standards.*

**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 defined is the real-world physical entity?
* 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 environmental parameters (e.g., temperature, pressure, operational context) influencing the physical system captured?

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

* How accurately does the system represent the physical entity within its specific application context, considering the data source and environment?
* 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 a user interface that allows users to interact, access its information and run analysis or experiments?
* How easily can the system be used by someone other than the person that created it?

**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 (regarding the scope that was decided) **[References !!!!]**.

**2.1 Bidirectional Data Flow**

**Physical-to-Virtual Connection:**

* How much human intervention is required for the system’s functioning? Is it self-regulating, self-monitoring, and self-diagnosing?
* On a scale from 0 (being no updates) to 5 (real time synchronization) how often is the data transmitted from the physical to the virtual system?
* How well is the system connected to other relevant systems within the same virtual/cloud environment?
* Are system parameters linked to real-world data and context?

**Virtual-to-Physical Feedback:**

* How seamlessly, within the scope of the system application, can it initiate interaction or changes in the physical entity? (0 being no reaction, 5 being sending control commands or notifications to humans in the loop)
* Is there a mechanism for real-time decision-making feedback to optimize physical operations?

**2.2 Synchronization**

**State Synchronization:**

* Is the connection method to the physical system identifiable and clear (e.g., sensors, management systems, online databases, IoT devices)?
* How often does the system synchronize the virtual representation with data from the physical object? (0 being never, 1 on start-up, 2 on demand, 4 periodically, 5 real time)
* How well is the sync update interval suited for the required decision-making process?

**Historical and Predictive States:**

* How well can historical, current, and predicted states be reflected dynamically?
* Is predictive synchronization integrated with (AI) models to anticipate operational behavior?

**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 that supports modeling and calculating capabilities required for decision making and control?
* Can the system evaluate "what-if" scenarios for varying operational settings?
* Does it enable predictive and prescriptive analysis?

**Optimization:**

* Are optimization algorithms applied to improve performance metrics (e.g., energy, logistics, costs, sustainability)?
* How well can trade-offs be analyzed in a wholistic point of view (e.g., sustainability vs. cost efficiency)?
* Does the system provide actionable insights for humans in the loop?

**3.2 Autonomy**

**Autonomous Actions:**

* To what extent does the DT autonomously monitor and diagnose faults in the system?
* To what extent does the system update itself without external intervention (representation, logic and parameters)?
* How well does the DT communicate with external systems?
* How well can the system independently make and execute decisions within its predefined perimeter?

**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:**

* How well is the system integrated with physical environment (ERP, MES, PLM, WMS, IoT, sensors …)?
* To what extent are multiple data sources (dynamic sensor data, static data, predictive results) fused for holistic insights?
* How well is data heterogeneity managed (handling different formats, resolutions, or sources)?
* How effectively does the DT integrate multi-modal data (structured vs. unstructured, historical vs. real-time)?
* What is the frequency of data updates from IoT devices, sensors, and systems? (Rarely | Occasionally | Periodically | Frequently | Continuously)
* Does the digital twin have access to historical data?

**5. Learning and Adaptability**

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 dynamically recognize environmental changes?
* How well does the system incorporate component interactions, disruptions, and uncertainties into its models? (Not considered | Poorly handled | Partially accounted for | Well accounted for | Fully integrated real-time modeling)

**5.2 Learning Capabilities**

**AI and Machine Learning:**

* How intelligent is the system in terms of self-learning and adaptation? (No intelligence | Basic rule-based logic | Limited machine learning | Adaptive AI | Fully autonomous learning system)
* To what extent does AI/ML contribute to predicting, analyzing, and optimizing the system’s performance over time? (No AI | Basic analysis | Some AI-based prediction | Strong AI optimization | Fully autonomous AI-driven decision-making)
* To what extent can the DT learn from past experiences and adapt to new situations? (No learning | Minimal adaptation | Partial adaptation | Strong adaptation | Fully autonomous self-evolving system)

**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 (design, operation, maintenance, end-of-life)? (Limited to one phase | Some lifecycle stages | Most lifecycle stages | Fully adaptable across all stages)

**Cognitive Capabilities:**

* To what extent can the system reason and make decisions autonomously?
* How interpretable and explainable are the DT’s decisions? (Not interpretable | Poor transparency | Some explainability | Strong explainability | Fully explainable AI-driven decisions)

(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:**

* To what extent is the model fidelity appropriate for the goals and use case (calibrated and validated DT)?
* To what extent are uncertainties or tolerances in the virtual model quantified and managed? (Not considered | Weakly estimated | Somewhat quantified | Well-quantified | Fully managed uncertainty modeling)

**Trust and Confidence:**

* How predictable is the system in interpreting its state, behavior, and functionality quantitatively and qualitatively? (Not at all | Weak interpretation | Moderate analysis | Strong predictive capability | Fully predictable across all states)
* 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 verification methodology (statistical testing, sensitivity analysis, real-world comparisons)? (Not applied | Weak testing | Some methods used | Extensive verification | Fully standardized multi-method validation)

**Continuous Improvement:**

* How effectively are real-world outcomes used for model refinement and enhanced predictions? (Not used | Weak feedback loop | Partial model adjustments | Strong model refinements | Fully self-improving adaptive system)
* How frequently does the DT incorporate new learnings into its models? (Never | Occasionally | Periodically | Frequently | Continuously self-updating)
* To what extent does the DT automatically adjust based on real-time validation feedback? (No adaptation | Limited adjustments | Partial self-improvement | Strong adaptation | Fully autonomous model evolution)

**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 system's performance and resilience (Jones et al., 2020).

**Monitoring and Real-Time Feedback:**

* To what extent does the system provide real-time monitoring of key metrics (e.g., energy, performance, errors)?
* How portable is the system? (0 – Not at all, single-device solution | 1 – Available on specific platforms | 2 – Limited cross-platform | 3 – Multi-device accessibility | 4 – Fully available across devices | 5 – Cloud-based, universally accessible)

**Failure Analysis, Prediction and optimisation:**

* How effectively does the system use data analysis techniques to identify patterns, detect anomalies, or predict failures?(Not at all | Weak detection | Moderate accuracy | Strong accuracy | Fully predictive analytics)
* To what extent can the system forecast future states and emergency events for proactive decision-making? (Not at all | Weak forecasting | Moderate trend analysis | Strong foresight | Fully AI-driven predictive analytics)
* To what extent does the system support predictive and prescriptive analytics?
* How well is operational optimization enabled in real-time?

**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 can advanced technologies (IoT, edge/cloud computing, AI/ML, big data, 5G) be employed? (Not at all | Weak integration | Some technologies used | Strong multi-tech stack | Fully multi-tech stack)
* Does the platform allow domain experts to develop and operate a DT without requiring deep technical knowledge?

**Scalability:**

* How capable is the system of interacting with other modules and platforms?
* Can the system handle increasing data volumes and expanding functionalities seamlessly? (Not scalable | Limited scalability | Moderate data handling | Strong scaling capabilities | Fully cloud-scalable and self-adapting)

**Security and Data Privacy:**

* How well are cybersecurity risks, data privacy, and evolving regulations addressed? (Not addressed | Weak security measures | Basic compliance | Strong security | Fully compliant with regulations and AI-driven security controls)
* What protective measures are in place to guarantee data privacy? (None | Basic authentication | Role-based access | Multi-level privacy control | Fully AI-powered privacy enforcement)
* Does the system ensure data privacy by preventing unauthorized access?