1 Digital Twin definitions

Table 1 presents the set of definitions on the Digital Twin concept that have been collected from the literature. For each of them, the authors, the publication year, the definition itself and the reference to the paper where it was published are shown.

Authors	Year	Definition	Reference
Shafto et al.	2010	An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The digital twin is ultra-realistic and may consider one or more important and interdependent vehicle systems.	[1]
Tuegel et al.	2011	A reengineering of structural life prediction. An ultrahigh fidelity model of individual aircraft by tail number.	[2]
Glaessgen and Stargel	2012	An integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin. The Digital Twin is ultra-realistic and may consider one or more important and interdependent vehicle systems, including airframe, propulsion and energy storage, life support, avionics, thermal protection, etc.	[3]
Tuegel	2012	A cradle-to-grave model of an aircraft structures ability to meet mission requirements, including submodels of the electronics, the flight controls, the propulsion system, and other subsystems.	[4]
Majumdar et al.	2013	Structural model which will include quantitative data of material-level characteristics with high sensitivity.	[5]
United States Air Force	2013	A virtual representation of the system as an integrated system of data, models, and analysis tools applied over the entire life cycle on a tail-number unique and operator–by-name basis.	[6]
Lee et al.	2013	A coupled model of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data-driven analytical algorithms as well as other available physical knowledge.	[7]
Reifsnider and Majumdar	2013	Ultra-high fidelity physical models of the materials and structures that control the life of a vehicle.	[8]
Hochhalter et al.	2014	A life management and certification paradigm whereby models and simulations consist of as-built vehicle state, as-experienced loads and environments, and other vehicle-specific history to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives.	[9]
Grieves	2014	The concept model contains three main parts: physical products in Real Space, virtual products in Virtual Space, and the connections of data and information that ties the virtual and real products together.	[10]
Rios et al.	2015	Product digital counterpart of a physical product.	[11]
Bazilevs et al.	2015	High-fidelity structural model that incorporates fatigue damage and presents a fairly complete digital counterpart of the actual structural system of interest.	[12]
Defense Acquisition University	2015	An integrated multiphysics, multiscale, probabilistic simulation of an as-built system, enabled by Digital Thread, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin.	[13]
Rosen et al.	2015	Very realistic models of the process current state and its behavior in interaction with the environment in the real world.	[14]
Bajaj et al.	2016	An unified system model that can coordinate architecture, mechanical, electrical, software, verification, and other discipline-specific models across the system life cycle, federating models in multiple vendor tools and configuration-controlled repositories.	[15]

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Authors	Year	Definition	Reference
Boschert and Rosen	2016	A comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all—the current and subsequent—lifecycle phases. This description can be made by means of a set of well aligned executable models with the following characteristics: (1) The Digital Twin is the linked collection of the relevant digital artefacts including engineering data, operation data and behaviour descriptions via several simulation models. The simulation models making-up the Digital Twin are specific for their intended use and apply the suitable fidelity for the problem to be solved. (2) The Digital Twin evolves along with the real system along the whole life cycle and integrates the currently available knowledge about it. (3) The Digital Twin is not only used to describe the behaviour but also to derive solutions relevant for the real system.	[16]
Grieves and Vickers	2016	A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin.	[17]
Schroeder et al.	2016	Virtual representation of a real product in the context of cyber-physical systems.	[18]
Gabor et al.	2016	The simulation of the physical object itself to predict future states of the system.	[19]
Kraft	2016	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by digital thread, which uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin.	[20]
Schluse and Rossmann	2016	Virtual substitutes of real-world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the Internet of things and services.	[21]
Leiva	2016	Refers to a digital model of a particular asset that includes design specifications and engineering models describing its geometry, materials, components and behavior. More important, it also includes the as-built and operational data unique to the specific physical asset that it represents.	[22]
Abramovici et al.	2016	A model that integrates interdisciplinary (mechanics, electronics, software, and services) virtual product models and related real-time data of a product instance (physical twin). A virtual twin can be dynamically generated from a model and data space to fulfill a specific task (e.g., dynamic reconfiguration of a smart product during its use phase).	[23]
Kuhn	2017	Digital representations of things from the real world. They describe both physical objects and non-physical things such as services, by making all relevant information and services available via a uniform interface. For the digital twin, it is irrelevant whether the counterpart already exists in the real world or will exist in the future. Digital twins are more than pure data. They contain algorithms that accurately describe their real-world counterpart, being often simulation models.	[24]
Banerjee et al.	2017	Computerized clones of physical assets that can be used for in-depth analysis.	[25]
Erikstad	2017	A digital model capable of rendering state and behaviour of a unique real asset in (close to) real time.	[26]
Tao and Zhang	2017	A reference model to realize the convergence between physical and virtual spaces. It combines the physical entity with high-fidelity virtual counterpart and the two parts company with each other during the lifecycle. The virtual part not only records the history performances of the physical one, but also carries out optimization and prediction for it. Meanwhile, the physical part provides its properties, behaviors and rules for the virtual mirror to make it calibrated and evolved continuously.	[27]

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Authors	Year	Definition	Reference
Negri et al.	2017	The virtual and computerized counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field.	[28]
Post et al.	2017	A representative of the real world and must be able to fully simulate all relevant behavior of the product/process during the life cycle, or a subset of this.	[29]
Alam and Saddik	2017	An exact cyber copy of a physical system that truly represents all of its functionalities.	[30]
Tao et al.	2017	An integrated multi-physics, multiscale, and probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin. The idea and concept of digital twin, which is composed of physical product, virtual product, and connected data that ties physical and virtual product, can realize the convergence between product physical and virtual space.	[31]
Uhlemann et al.	2017	Near real time linked simulation of the production system for continuous data acquisition.	[32]
Schleich et al.	2017	The vision of a bi-directional relation between a physical artifact and the set of its virtual models. In this context, the virtual "twinning," i.e., the establishment of such relations between physical parts and their virtual models, enables the efficient execution of product design, manufacturing, servicing, and various other activities throughout the product life cycle.	[33]
Stark et al.	2017	The digital representation of a unique asset (product, machine, service, product service system or other intangible asset), that compromises its properties, condition and behaviour by means of models, information and data.	[34]
Vachalek et al.	2017	A functional system of continuous process optimization, which is formed by the cooperation of physical production lines with a digital copy.	[35]
Zhang et al.	2017	A digital copy of the physical system to perform real-time optimization.	[36]
Brenner and Hummel	2017	A digital copy of a real factory, machine, worker etc., that is created and can be independently expanded, automatically updated as well as being globally available in real time.	[37]
Vrabic et al.	2018	A digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualized in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making.	[38]
Bruynseels et al.	2018	A specific engineering paradigm, where individual physical artifacts are paired with digital models that dynamically reflects the status of those artifacts.	[39]
Kunath and Winkler	2018	An ultra-realistic, high scaling simulation, which uses the best available physical models, sensor data and historical data for mirroring one or more real systems.	[40]
Kritzinger et al.	2018	Digital counterparts of physical objects.	[41]
Kumar et al.	2018	Virtual representation for various physical, mechanical, electrical, and electronics assets and artefacts.	[42]
Nikolakis et al.	2018	This rich digital representation of real-world objects/subjects and processes, including data transmitted by sensors, is known as the digital twin model.	[43]
Demkovich et al.	2018	A multi-level digital layout that describes the product, processes and resources in the environment of their functioning, i.e. allowing to simulate the processes taking place in the real system, as well as collecting and displaying in real time data on the status of objects obtained from the PLC and sensors installed in the production system both on industrial equipment and in its environment.	[44]

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Authors	Year	Definition	Reference
Haag and Anderl	2018	A comprehensive digital representation of an individual product that will play an intregral role in a fully digitalized product life cycle.	[45]
Tao et al.	2018	A reference model for the physical-virtual convergence.	[46]
Luo et al.	2018	A multi-domain and ultrahigh fidelity digital model integrating different subjects such as mechanical, electrical, hydraulic, and control subjects.	[47]
Schluse et al.	2018	A one-to-one virtual replica of a technical asset (e.g., machine, component, and part of the environment). A digital twin contains models of its data (geometry, structure, ...), its functionality (data processing, behavior, ...), and its communication interfaces.	[48]
Wang et al.	2018	A unique living model of the physical system with the support of enabling technologies including multi-physics simulation, machine learning, AR/VR and cloud service, etc.	[49]
Qi and Tao	2018	Is to create the virtual models for physical objects in the digital way to simulate their behaviors.	[50]
Liu et al.	2018	A living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information and can forecast the future of the corresponding physical counterpart.	[51]
Saddik	2018	Digital replications of living as well as nonliving entities that enable data to be seamlessly transmitted between the physical and virtual worlds. Digital twins facilitate the means to monitor, understand, and optimize the functions of all physical entities and for humans provide continuous feedback to improve quality of life and well-being.	[52]
Talkhestani et al.	2018	A virtual model of a physical asset capable of fully mirroring its characteristics and functionalities during its entire lifecycle. It is an approach to manage all generated digital data of a component or system along its lifecycle and retrieve them as needed by simulation or optimization functions to address any occurring challenges.	[53]
Zheng et al.	2018	A set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level.	[54]
Tao et al.	2018	A bridge between the physical world and the digital world. DT is characterised by the two-way interactions between the digital and physical worlds, which can possibly lead to many benefits. On one hand, the physical product can be made more intelligent to actively adjust its real-time behaviour according to the recommendations made by the virtual product. On the other hand, the virtual product can be made more factual to accurately reflect the real-world state of the physical product.	[55]
He et al.	2018	A dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole life cycle. The backbone technology of digital twin is the IoT for realtime and multisource data collection. In addition, it integrates artificial intelligence and software analytics to create digital simulation models that dynamically update and change along with their physical counterparts.	[56]
Madni et al.	2019	A virtual instance of a physical system (twin) that is continually updated with the latters performance, maintenance, and health status data throughout the physical systems life cycle.	[57]
Millwater et al.	2019	A high-fidelity, multiphysics, and multiscale structural model that will utilize the as-built geometry and material properties and as-experienced loading, and incorporate sensor data, maintenance and fleet history.	[58]

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Authors	Year	Definition	Reference
Hicks	2019	An appropriately synchronised body of useful information (structure, function, and behaviour) of a physical entity in virtual space, with flows of information that enable convergence between the physical and virtual states. The Digital Twin can exist at any stage of the life-cycle and aims leverage aspects of the virtual environment (high-fidelity, multi-physics, external data sources, etc.), computational techniques (virtual testing, optimisation, prediction, etc.), and aspects of the physical environment (historical performance, customer feedback, cost, etc.) to improve elements of the product (performance, function, behaviour, manufacturability, etc.) over the life-cycle.	[59]
Barricelli et al.	2019	Physical and/or virtual machines or computer-based models that are simulating, emulating, mirroring, or twinning the life of a physical entity, which may be an object, a process, a human, or a human-related feature. Each DT is linked to its physical twin through a unique key, identifying the physical twin, and therefore allowing to establish a bijective relationship between the DT and its twin. A DT is more than a simple model or simulation. A DT is a living, intelligent and evolving model, being the virtual counterpart of a physical entity or process. It follows the lifecycle of its physical twin to monitor, control, and optimize its processes and functions. More specically, the twinning process is allowed by the continuous interaction, communication, and synchronization (closed-loop optimization) between the DT, its physical twin and the external, surrounding environment. Descriptive data are continuously exchanged and updated thanks to the (nowadays-affordable) real-time data uploading and big data storage capabilities.	[60]
Lim et al.	2019	A high fidelity virtual replica of the physical asset with real-time two-way communication for simulation purposes and decision aiding features for product service enhancement.	[61]
Stark and Damerau	2019	A digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases.	[62]
Wang et al.	2019	A paradigm by means of which selected online measurements are dynamically assimilated into the simulation world, with the running simulation model guiding the real world adaptively in reverse.	[63]
Rasheed et al.	2020	A virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling and improved decision making.	[64]
Becue et al.	2020	Replicas of the physical manufacturing assets, providing means for the monitoring and control of individual assets. They can also be defined as simulation-based decision-support tools.	[65]
Lu et al.	2020	A digital replica of physical assets, processes and systems. DTs integrate artificial intelligence, machine learning and data analytics to create living digital simulation models that are able to learn and update from multiple sources, and to represent and predict the current and future conditions of physical counterparts.	[66]
Fuller et al.	2020	The effortless integration of data between a physical and virtual machine in either direction.	[67]
Digital Twin Consortium	2020	A virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. Digital Twin Systems transform business by accelerating holistic understanding, optimal decision-making, and effective action. Digital Twins use real-time and historical data to represent the past and present and simulate predicted futures. Digital Twins are motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented in IT/OT systems.	[68]

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Authors	Year	Definition	Reference
Lu et al.	2020	A high-fidelity representation of the operational dynamics of its physical counterpart, enabled by near real-time synchronization between the cyberspace and physical space.	[69]
Minerva et al.	2020	A comprehensive software representation of an individual physical object. It includes the properties, conditions and behaviors of the real-life object through models and data. A Digital Twin is a set of realistic models that can simulate an object's behavior in the deployed environment. The Digital Twin represents and reflects its physical twin and remain its virtual counterpart across the object's entire lifecycle.	[70]
Mostafa et al.	2020	A digital replication of various physical assets such as machines, people, functional areas, and the surrounding physical circumstances can be utilized to track, monitor, and intelligently predict for analytics, maintenance, and diagnostics purposes that leverages IoT technologies and able to react to the user fired or automatically triggered adjustments of its configurations. The entire suit of physical assets that the digital twin replicates is called its physical twin.	[71]
Jacoby and Usländer	2020	The virtual representations of resources organizing and managing information and being tightly integrated with artificial intelligence, machine learning and cognitive services to further optimize and automate production.	[72]
Trauer et al.	2020	A virtual dynamic representation of a physical system, which is connected to it over the entire lifecycle for bidirectional data exchange.	[73]
Jones et al.	2020	A means of improving the performance of physical entities through leveraging computational techniques, themselves enabled through the virtual counterpart.	[74]
Zohdi	2020	A digital replica of a physical system, where the philosophy is that updates to digital twins are made continuously in near real-time.	[75]
Malakuti et al.	2020	A formal digital representation of some asset, process or system that captures attributes and behaviors of that entity suitable for communication, storage, interpretation or processing within a certain context. The digital twin information includes, but is not limited to, combinations of the following categories: physics-based model and data, analytical models and data, time-series data and historians, transactional data, master data, visual models and computations.	[76]
Agnusdei et al.	2021	Where digital models and physical ones communicate – by sharing data as well as information – usually in a bidirectional way. DTs could be considered an evolution of complex simulation models. They are based on a digital replica of a physical object (twin) and are deeply integrated with IOT technologies.	[77]
Qi et al.	2021	A unique means to achieve the cyber-physical integration. DT means an organic whole of physical asset (or physical entity) as well as its digitized representation, which mutually communicate, promote, and co-evolve with each other through bidirectional interactions.	[78]
Singh et al.	2021	A dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data. It is not just the Digital Twin which mimics its physical twin but any changes in the Digital Twin are mimicked by the physical twin too.	[79]

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Authors	Year	Definition	Reference
Eigner et al.	2021	The digital representation of a unique physical or non-physical product, process, or service from the real world in the digital world. It includes all information from the digital model required for a specific use case and all data collected throughout all lifecycle phases, disciplines, and relevant IT systems. The digital twin core is created, either during prototype construction based on the current configuration status, during development, or after production based on an as-built or as delivered bill of materials. Depending on the requirements of the use case, the digital twin core can be reduced or enriched with additional information from any source.	[80]
ISO Central Secretary	2021	Fit for purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation. An observable manufacturing element refers to an item that has an observable physical presence or operation in manufacturing, including personnel, equipment, material, process, facility, environment, product, and supporting document.	[81]
Liu et al.	2021	A digital entity that reflects physical entity's behavior rule and keeps updating through the whole lifecycle.	[82]
VanDerHorn and Mahadevan	2021	A virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems.	[83]
Voas	2021	The electronic representation -the digital representation- of a real-world entity, concept or notion, either physical or perceived.	[84]

Table 1: Collection of Digital Twin definitions gathered from the currently available literature.

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