Basic Technologies and Models for Implementation of Industry 4.0

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Digital Twin: Background, Challenges, Enabling Technologies, Benefits, and Use Case in the Elevator Industry

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Abstract: *Digital twins represent a new paradigm that brings fundamental changes to business and asset management. The proliferation of connected devices and sensors has generated vast amounts of data from physical assets and processes. Digital twins leverage this data to create a virtual counterpart that reflects the behavior, performance, and characteristics of their physical counterparts in real-time. The definition of digital twins encompasses a wide range of applications and contexts. This paper provides an overview of existing literature on digital twins, including their definition, key characteristics, and classification. Additionally, it highlights potential challenges and limitations associated with digital twins and identifies the technologies that enable their implementation. By understanding the fundamental concepts and technological advancements in the field of digital twins, organizations can harness their potential to enhance their business, optimize resources, and foster innovation. Numerous examples of digital twin applications in various industries are highlighted in this paper, with a particular focus on the elevator industry.*
Therefore, this paper serves as a comprehensive source of information for researchers, practitioners, and decision-makers who wish to explore the application of digital twins in different industries and domains.

Keywords: *Digital twin, benefits, challenges, enabling technologies, use cases*

1. Introduction

Digital twins have proven to be valuable in a wide range of domains, including manufacturing, healthcare, infrastructure, and smart cities. By creating virtual replicas, businesses can benefit from real-time insights, operational optimization, reduced downtime, and substantial cost savings.
Adopting digital twins provides organizations with business growth, enables them to effectively respond to evolving market dynamics and maintain industry leadership. Digital twins serve as enablers of data-driven decision-making by providing a platform to simulate various scenarios in a virtual environment,

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which provides businesses with extraordinary opportunities to test and fine-tune strategies before implementing them in the physical domain. Consequently, digital twins facilitate informed decision-making, mitigate risks and encourage exploration of innovative approaches, leading to improved results and competitive advantage.

In addition to their manifold advantages, digital twins are not without the challenges. These challenges encompass various aspects, including the acquisition and integration of data from disparate sources, concerns surrounding data security and privacy, computational demands, and the necessity for precise modeling and simulation. Furthermore, the successful deployment of digital twins necessitates careful consideration of factors such as interoperability, scalability, and the potential disruption of existing workflows.

A comprehensive understanding of the characteristics and classifications of digital twins is pivotal for their effective implementation. Equally important are the enabling technologies that play a crucial role in the development and utilization of digital twins. Data acquisition technologies, including sensors and Internet of Things devices, form the fundamental infrastructure for capturing real-time data. Advanced analytics techniques, machine learning algorithms, and simulation tools facilitate data processing, analysis, and the creation of virtual representations.Visualization technologies, such as virtual reality and augmented reality, contribute to an enriched user experience and enable seamless interaction with digital twins. These technologies provide immersive and interactive interfaces that enhance the understanding and utilization of digital twins. Their application spans across diverse domains, including manufacturing optimization, healthcare advancements, and infrastructure performance enhancement, showcasing the versatile potential of digital twins.

Regarding the future of digital twins, research conducted by Allied Market Research and Markets and Markets indicates significant growth in the digital twin market in the coming years. The global digital twin industry was valued at $6.5 billion in 2021 and is projected to reach $125.7 billion by 2030 [1]. Markets and Markets also forecast a market opportunity for digital twins to increase from $6.9 billion in 2022 to $73.5 billion by 2027 [2]. According to Allied Market Research, system digital twinsare expected to have a dominant share in the market during the forecast period. This is attributed to their widespread adoption, particularly in industries such as automotive, electrical, gas, and energy. Product digital twins rank second in terms of market share, followed by process digital twins. The report highlights that the automotive and transportation industries held the largest market share for digital twins in 2021, followed by aerospace, retail, energy, and oil & gas sectors.

The digital twin serves as a fundamental component in the construction of the metaverse. These virtual representations intricately mimic real-world objects, and the next evolution of digital twins will feature photorealistic graphics,

physics-based simulations, artificial intelligence integration, and interconnectedness within metaverse ecosystems [3].
The accuracy and reliability of digital twins are supreme. The high degree of reliability ensures that digital twins closely replicate the behavior and characteristics of their real-world counterparts, enabling robust predictive capabilities. Organizations are tasked with capturing comprehensive data related to a physical object and then seamlessly integrating the real-time information into their digital twin systems. In this way, the digital twin remains in sync with its physical counterpart, improving its capabilities and overall efficiency.

2. Background, Definition, Characteristics and Classification

The inception of the Digital Twin concept can be traced back to the collaborative endeavors of Michael Grieves from the University of Michigan and John Vickers of NASA. In 2002 Grieves first introduced the ''Conceptual Ideal for PLM'' which encapsulated all the essential elements that define the Digital Twin: the real space, the virtual space, the critical link enabling the seamless flow of data from the real space to the virtual space, the reciprocal exchange of information from the virtual space to the real space, and the existence of virtual sub-spaces. In later works, Grieves [4] used a model named the Mirror Space model.

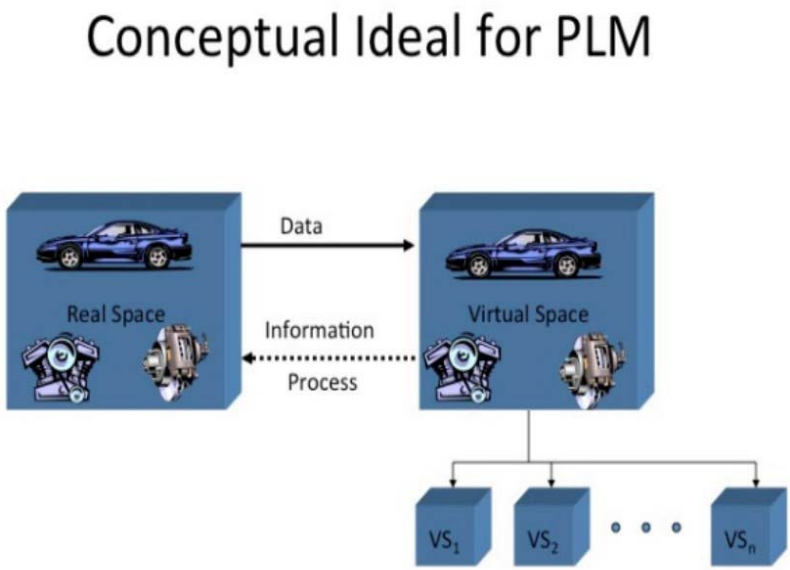

Figure 1. Conceptual ideal for PLM by M. Grieves

The aerospace industry, especially NASA, played a vital role in the development of digital twins. NASA pioneered the use of virtual models and simulations to replicate and monitor the behavior of spacecraft and satellites, referred to as ‘’mirror models’’. During the Apollo 13 mission, NASA utilized simulators and integrated digital components into a physical model of the spacecraft following an oxygen tank explosion. As Stephen Ferguson [5] explained, this incident illustrates key characteristics of digital twins, such as the physical model, adaptability, connectivity, and responsiveness. Digital twins are effective when dealing with physical assets that are temporarily inaccessible for direct human intervention, as was the case with Apollo 13. Furthermore, constant feedback from the physical asset is crucial for updating the digital twin’s condition and informing engineering decisions, a requirement NASA achieved through advanced telecommunications. Nowadays, the Internet of Things is commonly used for the purpose of connectivity. Additionally, digital twins should be adaptable to changes in the physical asset, and NASA demonstrated this through rapid reconfiguration of simulations to provide critical information during the mission. Moreover, NASA utilized multiple interconnected models, indicating that modern digital twins are not solely based on a comprehensive single model but can combine different models to account for various aspects of performance. Lastly, the swift response of the digital twin to the events of Apollo 13 showcases its ability for rapid implementation and adaptation after critical damage to physical assets.These digital representations significantly enhanced mission planning, performance analysis, and diagnostics.

The term ‘’Digital Twin’’ was first mentioned in NASA’s draft version of the technological roadmap [6]. Interestingly, although the term emerged in the 2010 roadmap, NASA had previously implemented a similar concept during the Apollo program, constructing two identical space vehicles to mirror each other. A clearer overview of the evolution of digital twins is provided in Figure 2.

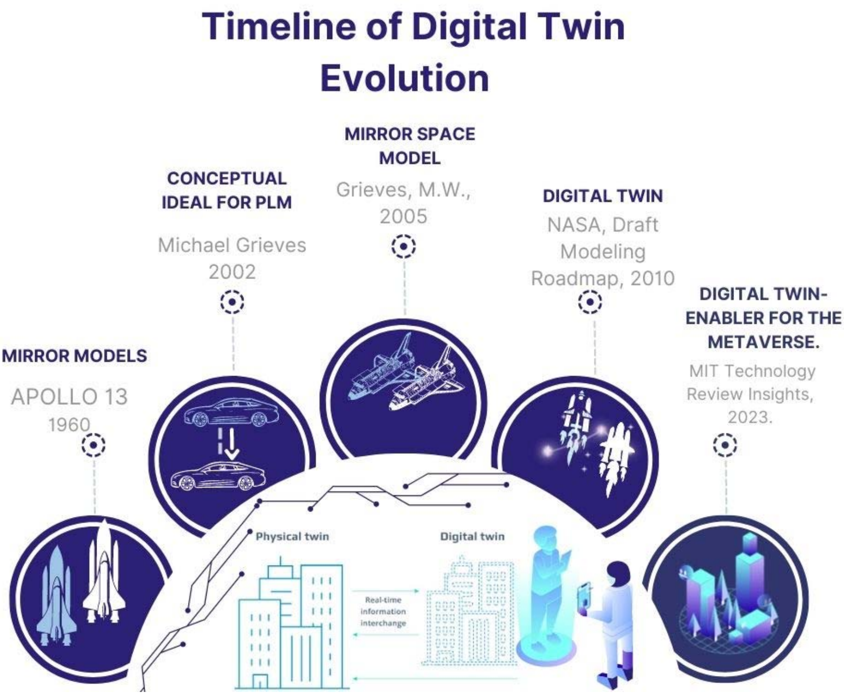

Figure 2. Timeline of digital twin evolution

Today, different authors describe the digital twin in various terms. Therefore, definitions are referring to the digital twin as a simulation, technological framework, description of a component, virtual representation, informational construct, digital footprint, links, virtual and digital model, digital mirror, replica, and digital representation of its physical counterparts. These various terms and descriptions in the literature reflect the diverse perspectives and applications of digital twin, emphasizing its role as a digital representation, counterpart, or simulation of the physical entity.

Table 1. Digital twin definitions

DIGITAL TWIN DEFINITIONS		
Authors, Year	**Definition**	**Terms**
Glaessgen, E.; Stargel, D. (2012)	''The Digital Twin integrates ultra-high fidelity simulation with the vehicle s on-board integrated vehicle health management system, maintenance history and all available historical and fleet data to mirror the life of its flying twin and enable unprecedented levels of safety and reliability''.[41,1818 p.]	Simulation
Shafto, M. et.al. (2010)	''A digital twin is 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''. [6., 7. p.]	
Tao, F., Cheng, J., Qi, Q. et al. (2018)	''Digital twin is 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''. [42, 3564 p.]	
Gabor T., et.al. (2016)	''These ultra-high fidelity simulations are commonly called a digital twin with respect to the system they model''.[44, 374, p.]	
Zhuang, C., et.al. (2018)	''The proposed digital twin model enhances the ability to digitally simulate how the production line will perform in the real world''. [43]	
Trancossi M., et.al. (2018)	''Digital Twin is the technological framework that allows an effective lifecycle analysis of a system and an effective comparison of different configurations. It allows determining the digital model of a physical system and replicating its evolution''. [45,303, p.]	Technological framework

Boschert, S. and Rosen, R. (2016).	''The Digital Twin itself refers to 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''.[46,59, p.]	Description of a component,
Rasheed, A., et.al. (2020).	''A digital twin is defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making''.[47, 21998, p.]	Virtual representatio n
Kritzinger, W., et.al. (2018)	''The Digital Twin in its original form is described as a digital informational construct about a physical system, created as an entity on its own and linked with the physical system in question''. [14, 1016, p.]	Informational construct
Grieves, M. & Vickers, J., (2017)	''Digital Twin (DT)—the Digital Twin is 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''. [4, 94, p.]	
Mayani, M.G., et.al. (2018)	''Digital Twin refers to digital footprint of physical systems in the various assets which act like a bridge between physical and digital world''. [48, 1, p.]	Digital footprint
Dietz, M., & Pernul, G. (2019)	''The Digital Twin (DT) is an asset's virtual counterpart that enables enterprises to digitally mirror and manage an asset along its lifecycle''. [49, 1, p.]	Counterpart
Negri, E., et.al. (2017)	''The Digital Twin (DT) is meant as 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''. [50, 940, p.]	

Canedo, A. (2016)	‘’Digital Twins are a new mechanism to manage IoT devices and IoT systems-of-systems throughout their lifecycle’. [51, 1,p.]	Links
Barricelli, B., et.al. (2019)	‘’The DT is a virtual model of the physical object with the potential of understanding changes in the status of the physical entity through sensing data, to analyze, predict, estimate and optimize changes’’. [52, 1, p.]	Virtual model
Singh, M., et.al. (2021)	‘’A Digital Twin is 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’’. [8,5, p.]	Virtual/digital model
Guo, J., et.al. (2018).	‘’Digital twin is the digital mirror of the physical world and maps performance of physical world’’.[53,1, p.]	Digital mirror
Rajratna, K. et.al. (2018)	‘’Digital Twin can be defined as a replication of real physical production system in digital model, which are used for system optimization, monitoring, diagnostics and prognostics using integration of artificial intelligence, machine learning and software analytics with large volume of data from physical systems’’. [54, 7, p.]	Replica
Madni A.M., et.al. (2019)	‘’Digital twin is a dynamic digital representation of a physical system’’.[10,1,p]	Digital representatio n

Source: Authors systematization based on sources in the table

Characteristics of digital twin

The overarching goal is for the digital twin to be self-evolving in the sense that it continuously improves and optimizes its performance in line with the physical system it represents. Digital twins possess a broader set of characteristics that affect their operational and business value.

The first characteristic refers to the possibility of self-adaptation in the sense that it automatically responds to changes in the environment and configuration of its real twin, continuously striving for operational excellence measured by performance indicators adapted to the given case.

Another characteristic relates to self-regulation, ensuring that the changes it undergoes as it adapts to the true twin environment do not exceed the physical twin's limitations in order to maximize its performance measures, such as productivity and throughput.

Thirdly, the digital twin is always aware of the real twin's environment and configuration through self-monitoring of relevant parameters.

Finally, the digital twin is capable of self-diagnosing and evaluating its own health based on current and historical data to identify the reasons for any suboptimal operations.

Besides these characteristics mentioned by Mihai S., et al. [7] , other authors also highlight similar features of the digital twin. For instance, Singh, M. et al. [8] emphasize the fidelity of the digital twin, which refers to being an identical copy of its physical counterpart actually reflecting a high degree of accuracy and reliability in appearance, content, functionality, and behavior. The higher the fidelity, the more significant the impact on the quality of the simulation and the fidelity of the alternative scenarios. The dynamism of the digital twin is achieved through the exchange of dynamic, historical, statistical, and descriptive data in real-time. This, along with fidelity and hierarchy, ensures a realistic emulation of each component of the physical twin. Identification of each physical object throughout its product life cycle with relevant information and their interconnectivity are significant characteristics of a digital twin. The digital twin encompasses the multi-scale and multi - physical nature of the digital twin. Such as shape and size, surface roughness, structural dynamics, thermodynamics, stress analysis, fatigue damage modeling and material properties of the physical counterpart. Furthermore, digital twins possess the characteristic of multidisciplinarity as they integrate various disciplines and serve as the foundation of Industry 4.0.

Classification of Digital Twin

Various criteria, including the lifecycle phases, applications, hierarchy, and maturity level, can be used to classify digital twins into different types. The classification of digital twins is constantly expanding, as the number of dimensions that are taken into account increases with the possibilities of use.

The following Figure 3 shows the division of digital twins according to the available literature.

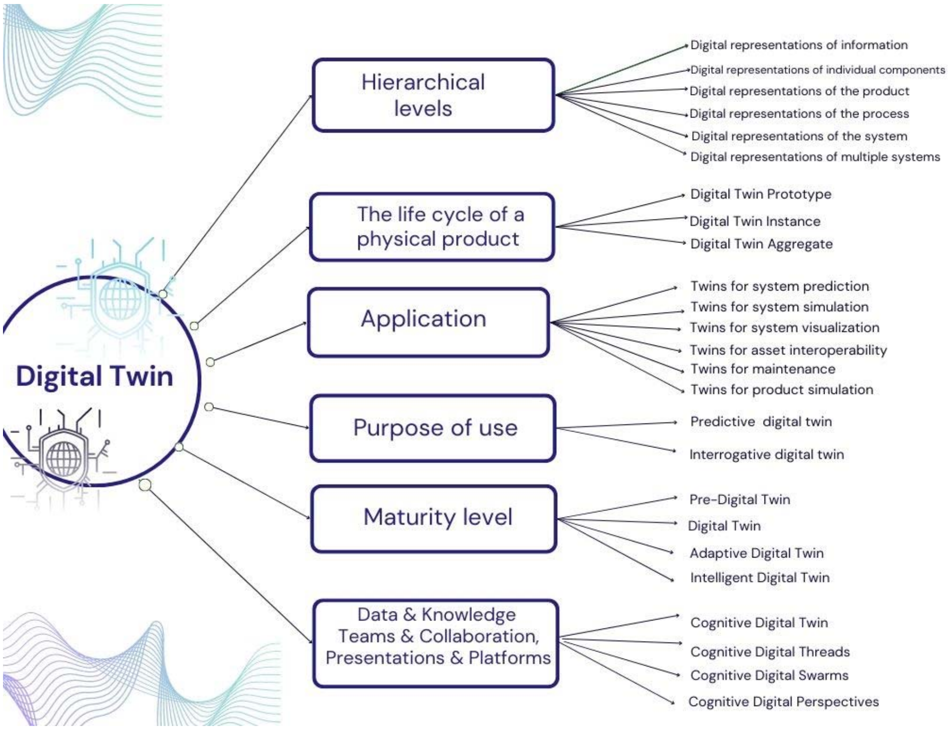

Figure 3. Classification of digital twin

According to IoT Analytics Research [9], digital twins can be classified based on three dominant dimensions: the hierarchical levels of application, the lifecycle phase of usage, and the specific application. These dimensions result in 252 potential combinations, each representing a unique classification of a digital twin.

Digital twins can be classified into six subcategories based on the hierarchical dimension. The informational level encompasses digital representations of information, such as an operation manual in digital format. The component level represents digital representations of individual parts or components of a physical object. The product level relates to digital representations of the interoperability of components at the product level. The process level includes digital representations of entire processes and workflows. The system level involves digital representations of multiple processes and workflows, not limited to physical objects. Lastly, the multi-system level involves digital representations of multiple systems working together as a unified entity. These hierarchical levels enable comprehensive analysis and management of digital twins in various domains and contexts. Digital twins are applied in six lifecycle phases.In the design phase, requirements are gathered and designs are developed using digital twins as a source of data. The build phase involves creating software-based digital twins, eliminating the need for costly physical prototypes. During the operating phase, users utilize online digital twins for tasks like extracting sensor data or remote device control. The maintenance phase involves making changes to hardware, software, and documentation to ensure operational effectiveness. In the optimization phase, existing information is used to improve design, predict performance, and optimize operations. Finally, the decommissioning phase involves removing digital twin releases from use and retiring them remotely.

Based on the area of application IoT Analytics [28] distinguishes the following models of digital twins:

1. Twins for system prediction- used to predict complex systems.
2. Twins for system simulation- simulates complex systems.
3. Twins for asset interoperability- aimed at extracting data in complex systems and creating common data formats.
4. Twins for maintenance-helps maintain the system during its life cycle, enables predictive maintenance to avoid downtime.
5. Twins for system visualization -used for system visualization during the life cycle using 3D visual elements.
6. Twins for product simulation- used during design to simulate the behavior of the product to be developed.

According to sophistication in the level of maturity Madni A.M., et al. [10] listed four types of digital twins. At the first level is the pre-digital twin, a virtual system model created before the physical prototype, with the aim of mitigating technical risks. A virtual prototype is not used to construct the final system, but rather to make design decisions and manage risk in the early stages of the project. It can serve as a prototype to be discarded or reused in later stages of the project. At the second level, a digital twin encompasses the integration of performance, health, and maintenance data derived from its corresponding physical twin. Through interaction between the digital and physical twins, the information acquired from one or multiple digital twins can be harnessed by the physical twin to enhance its real-time performance. At this stage, the digital twin functions as a platform for comprehensive exploration of the behavior exhibited by the physical twin in various hypothetical scenarios, allowing for in-depth analysis and evaluation of potential outcomes. Its executable nature allows for easy manipulation and controlled simulation tests to investigate system behavior comprehensively. Identified deficiencies or shortcomings can be utilized to modify the physical twin. Level 3 introduces the adaptive digital twin, which introduces an adaptive user interface that caters to the needs of both the physical and digital twins, resembling the characteristics of a smart product. The user interface can be customized to accommodate user/operator preferences andpriorities, ensuring a personalized experience. At this level, a salient characteristic is the capacity to assimilate and discern the preferences and priorities of human operators within heterogeneous contexts, thereby enabling a personalized and contextually adaptive interaction. This learning process is achieved through the utilization of a supervised machine learning algorithm, employing a neural network architecture. Theutilization of adaptive digital twin empowers real-time planning and decision-making processes across operational, maintenance, and support activities, facilitating timely and informed actions based on current and evolving conditions. Moving to Level 4, the intelligent digital twin possesses all the capabilities of a Level 3 digital twin, including the incorporation of supervised machine learning techniques. Moreover, this level of advancement introduces the capability for unsupervised machine learning, facilitating the identification and recognition of objects and patterns encountered within the operational environment. Additionally, it enables enhanced learning of system states and environments characterized by uncertainty or limited visibility, thereby augmenting the digital twin's ability to adapt and respondeffectively to dynamic conditions.

Looking at the dimension of the lifecycle of a physical product, authors Grieves M. and Vickers J. [11], have made a distinction between digital twin prototype, digital twin instance and digital twin aggregate. Therefore, a digital twin prototype is a digital twin that contains the set of data and information that is essential to create or manufacture a physical copy of the virtual version. This marks the beginning of the product cycle, and once the digital twin prototype is completed and validated, the production of its physical twin can begin. The more accurate the simulation model used by this type of digital twin, the higher the quality of its physical twin will be. Digital twin instance is a digital twin that describes a specific corresponding physical product to which an individual digital twin remains connected throughout the lifecycle of that physical product. Both types of digital twins are integrated and operated in digital twin environment. Digital twin aggregate represents a collection of digital twins.

According to the purpose of use, the same authors distinguish between predictive and interrogative digital twins. The utilization of the digital twin encompasses the prediction of future behavior and performance of the physical product. Digital twin instances offer the capability to examine their current and past histories, regardless of the physical location of their counterparts worldwide. Individual instances can be interrogated to retrieve information about their present system state. By analyzing data from multiple product instances, correlations can be established to predict future states and outcomes.

Semantic technologies have emerged as critical components in numerous intelligent systems, facilitating semantic interoperability across disparate data and information sources. They offer promising solutions for integrating heterogeneous digital twin models within complex systems that span different

domains and lifecycle phases. By employing semantic modeling and knowledge graph modeling, the integration process becomes more efficient and effective, enabling a holistic understanding of the interconnected digital twins and enhancing the overall system's performance and functionality [12]. By combining semantic technologies with digital twins, El. Adl, A. [13], introduced the concept of a cognitive digital twins as a ‘’digital representation, augmentation, and intelligent companion of its physical twin as a whole, including its subsystems and across all of its life cycles and evolution phases’’.
Taking into account dimensions such as data and knowledge, teams and collaboration, presentations and platforms, the same author defines the following concepts:

1. Cognitive Digital Twin: refers to a purpose-driven digital representation of a physical twin that possesses the ability to continuously acquire knowledge and learn.
2. Cognitive Digital Threads: provides the right data at the right time, within the right context. It involves the integration of data and knowledge for both the physical and digital twins, creating a coherent and synchronized thread of information.
3. Cognitive Digital Swarms: this technical framework focused on the collaboration and interaction between teams of physical and digital twins, allowing for collective intelligence and decision-making.
4. Cognitive Digital Perspectives: it introduced an alternative framework for human-machine interface and man-machine interface that was suitable for cognitive systems, enabling a more intuitive and efficient interaction between humans and digital twins.

One of the most commonly cited classifications of digital twins into subcategories such as digital model, digital shadow, and digital twin, provided by the group of authors Kritzinger W. et al. [14], will not be specifically discussed in this paper due to the increasing criticisms it has received from both practitioners and researchers. The main criticisms of this classification revolve around its recursion, unclear definition of data types, ambiguity regarding why the manner in which data is transmitted should serve as the basis for differentiation, and a lack of utility in practical use [15].

3. Benefits, Challenges and Enabling Technologies

Digital Twin Benefits

Digital twins offer a multitude of benefits that vary based on specific use cases.Here, we will highlight the most important and commonly observed advantages regularly seen in practical applications:

1. **Shortening time and reducing costs in the phases of a product life cycle: -** Simulations enable the exploration of different scenarios, shortening

designand analysis cycles. This makes the entire process of prototyping or redesigning faster and easier. Digital twins utilize virtual resources for their creation, resulting in reduced overall prototyping costs over time. In contrast to traditional prototyping that involves physical materials and labor, digital twin allows for product recreation and testing without additional material expenses. Adamenko D., et.al. [16]state that process monitoring and diagnosis are widely acknowledged as significant benefits of a digital twin in enhancing the quality and identifying irregularities. This, in turn, enables more efficient maintenance strategies that can effectively reduce both costs and duration.

2. **Prediction of issues, improved maintenance, improved product, process, and system planning, prescriptive decision-making –** Digital twins enable the prediction of future issues and errors for the physical twin of a product. This provides the opportunity to plan systems according to anticipated problems, which is particularly useful for products with complex structures and multiple components. Digital twins allow for the optimization of solutions and maintenance strategies for products. Khajavi, S. H., et.al, [17] state a digital twin can provide data regarding the buildings' maintenance needs. Through simulating various scenarios, digital twin provides the best possible solution or maintenance strategy for products or systems. The continuous feedback loop between digital twins and the physical twin enables real-time validation and optimization of system processes.
3. **Mobility and increased safety compared to the physical twin. -** The physical device can be remotely controlled and monitored through its digital twin. Unlike physical systems that are limited by geographical location, digital twin can be shared and accessed remotely. This is particularly useful in situations where local access is restricted. In industries such as oil, gas, or mining, where working conditions are extreme and hazardous, digital twin can reduce the risk of accidents and dangerous malfunctions. According to Kaarlela, T. et.al., [18] the utilization of digital twins allows for the creation of safety training programs that are more effective and visually engaging compared to traditional methods. The ability for remote access and the predictive nature of digital twin can mitigate the risk of incidents.
4. **Improved performance and increased competitiveness of the company -** informed decision-making, risk mitigation, and the exploration of innovative approaches, ultimately leading to improved outcomes and competitive advantages.

Digital Twins challenges

The challenges of implementing digital twins are numerous and can be viewed from various perspectives. Their multiplication is certainly contributed to by the challenges of implementing the technologies of Industry 4.0 themselves, which are actually the technological enablers of digital twins. The most common challenges faced by companies, according to the literature, can be classified as follows:

1. **Investment cost:** Implementing digital twins solutions involves substantial costs for technology platforms, infrastructure development, maintenance, data quality control, and security solutions. Additionally, the ongoing operational expenses for maintaining the digital twin infrastructure can be significant. Attaran, M., & Celik, B. G. [19] emphasize that these high fixed costs and the complexity of the infrastructure will slow the adoption of digital twin technologies.
2. **Data management** refers totechnical, financial and legal aspects of data ownership and governance. Privacy and security pose significant challenges for digital twins in industrial settings due to the large volume of data they utilize and the potential risks to sensitive system data. To address this challenge, according to Fuller A., et.al.[20], it is crucial for the key enabling technologies of digital twins, namely data analytics and IoT, to adhere to up-to-date security and privacy regulations.
3. **IT infrastructure:** Two specific challenges that Fuller A., et.al., [20] discussed are the need for a well-planned IT infrastructure to support digital twins' success and the requirement for high-quality, consistent data to ensure optimal performance of the digital twin.
4. **Connectivity and integration:** The challenges of interoperability arise due to data-level issues, while the integration of digital twin models becomes more complex as a result. Semantic technologies and systems engineering offer potential solutions according to Zheng, X.,et. al.[12] by leveraging advanced tools like knowledge graphs to semantically connect digital models and represent their interrelationships using edges.
5. **Standardized and domain modeling:** Standardized modeling is a key challenge in the development of all types of digital twins, as there is currently no universally accepted approach. A standardized approach is necessary to ensure domain and user understanding, and facilitate information flow throughout the development and implementation stages of a digital twin. Domain modelingis crucial to transfer domain-specific information to each stage of digital twin modeling, ensuring compatibility with domains such as IoT and data analytics.Fuller A., et.al. [20] notice that this enables the effective utilization of the digital twin in various applications.
6. **Reliability and rate of synchronization:** The reliability of the virtual representation and the synchronization rate depends on the purpose of the digital twin. According to Mihai S., et al. [7] in certain applications, such as surgery or the aviation industry, high levels of reliability and synchronization are necessary. However, for traffic management and 3D visualization purposes, lower levels of reliability and synchronization can be sufficient.

7. **Cognitive capabilities:** The primary challenge facing Cognitive Digital Twins (CDTs) is achieving cognitive capabilities. Abburu S., et al. [21] identified three key challenges in CDT cognition: knowledge representation, knowledge acquisition, and knowledge updating. Knowledge representation refers to defining and standardizing relevant information and knowledge as input to digital models to ensure interoperability. For the representation of domain knowledge, existing domain standards, and collaboration between digital twins, the authors propose an ontology, and for the representation of problem-solving knowledge certain rules. Another challenge is gathering implicit knowledge, which is based on personal experience. NLP technologies such as text mining and speech recognition can help. In order to discover hidden knowledge from raw data following the flow of data-information-knowledge, data mining can also be used. Knowledge update is an ongoing process of continuously updating existing knowledge and generating new knowledge. It encompasses knowledge extension, knowledge forgetting, and knowledge evolution. The main challenge is to maintain consistency after implementing changes and, more importantly, to identify the right timing for incorporating changes. In addition to this limitation of the cognitive digital twin, Zheng, X.,et al. [12] also point out the challenges of integrating digital twins, the lack of standardization, and implementation difficulties.

Digital twin enabling technologies

Digital twins require specific enabling technologies that vary depending on the intended use case. One crucial aspect is establishing a communication medium between the physical and digital twins. The selection of enabling technologies for digital twins involves careful consideration of communication protocols, algorithms, and frameworks that align with the specific requirements and objectives of the digital twin application. However, the choice of communication protocol depends entirely on the communication requirements of the specific digital twin application. Researchers and practitioners from diverse industries analyze and choose technologies that best suit their use cases to effectively develop and utilize digital twins in their endeavors.

The most common enabling technologies of the digital twin are illustrated in Fig. 4.

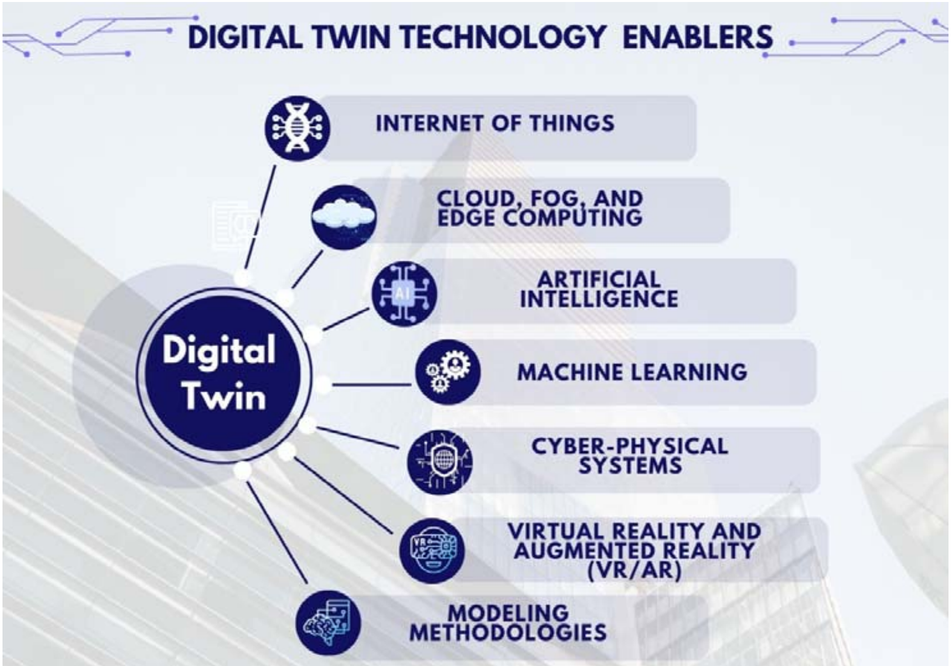

Figure 4. Digital twin: Enabling technologies

By leveraging AI/ML models, digital twins can replicate the behavior, characteristics, and interactions of their physical counterparts. This leads to a more detailed understanding of the underlying processes, as well as the ability to predict, optimize performance and support decision-making.

Cloud computing refers to the delivery of IT resources, including data storage, computing power, networking, and software, over the internet. Cloud computing plays a crucial role in the implementation of digital twin systems by providing a cost-effective and efficient solution without the delays typically associated with building infrastructure from scratch. Fog and edge computing provides a distributed computing infrastructure that complements cloud computing in the context of digital twins, enabling localized data processing and privacy preservation. In this case, not all data is transferred to the cloud and sensitive or critical data can be processed locally, ensuring data security and reducing bandwidth requirements. This is especially important in applications where privacy, security and compliance are crucial. They enable real-time processing, efficient use of resources, localized data processing and improved responsiveness.

The Internet of Things enables the seamless and real-time exchange of data between a multitude of physical devices via the Internet. Although a huge network, it is able to simplify the connection between physical entities and their virtual representations. The basis of the IoT ecosystem is made up of smart sensors whose role is the integration of traditional sensor technology with microprocessors and/or wireless communication units. This integration enables smart sensors to collect environmental data with precision and automation. By combining data collection capabilities with intelligent processing and communication functions, smart sensors contribute to accurate and efficient data collection, facilitating the development and use of digital twin systems. VR and AR technologies provide immersive and interactive experiences for physical-virtual twins. They enable visualization, communication and manipulation of virtual representations of physical systems, improving the understanding and control of complex processes. The use of VR/AR makes digital twins more accessible, engaging and efficient, as users can monitor critical data, explore virtual environments and operate equipment with the help of intuitive virtual interfaces.

Modeling enables the representation and management of physical entities in digital form. Geometric, physical, feature, behavioral, and rule modeling techniques are utilized to capture various aspects of the physical entity and facilitate analysis, simulation, reasoning, and optimization within the digital twin framework [22]. Geometric modeling focuses on capturing the geometric information of an entity, while physical modeling incorporates additional details such as accuracy, material properties, and assembly information. Feature modeling involves defining interactive features, automatically recognizing features, and enabling feature-based design. Behavioral modeling encompasses the representation of various behaviors exhibited by a physical entity to fulfill functions, respond to changes, interact with other entities, and adjust internal operations. Simulating physical behaviors involves multiple models, including problem models, state models, dynamics models, and evaluation models. Rule modeling involves extracting rules from historical data, expert knowledge, and predefined logic to equip the virtual model with reasoning, judgment, evaluation, optimization, and prediction capabilities. Rule modeling is a demanding task because it includes rule extraction, rule description, rule association, and rule evolution.

Digital Twin Platforms

Due to the costly and complex nature of digital twin development, technologically advanced companies offer platforms to assist other companies in developing their own digital twins for products, processes, or systems. These platforms provide valuable support and resources for organizations seeking to embrace the benefits of digital twin technology. The following section offers some information on these companies.

The Siemens digital twin platform, ''Xcelerator'' allows companies to create digital replicas of their products and systems, optimizing performance, reducing costs, and improving efficiency. Sweden's NEVS utilizes the Siemens Xcelerator platform to establish a digital thread and comprehensive digital twin for vehicle projects, emphasizing the significance of advanced simulation technology and a digital twin approach in creating safe self-driving mobility solutions. The outcomes include leveraging enhanced digital twin accuracy for sustainable mobility solutions and achieving a 50% reduction in initial vehicle assessment time, automation of simulation processes, and an 80% reduction in early-stage design option identification time [23].

The General Electric platform ''Predix'' enables companies to create and manage digital twins of their products, processes and systems and to analyze data from those twins to improve performance and efficiency. The primary focus of this platform lies in industrial applications, providing a range of tools specifically designed for constructing digital twins of industrial assets like turbines or factories. By using this platform, users can enable predictive maintenance, optimize performance, and gain valuable operational insights [24].

One perfect example of the utilization of digital twins in warehouses, particularly with NVIDIA Omniverse, has been instrumental in revolutionizing Amazon Robotics [25].By creating full-scale digital replicas of their warehouses, they have been able to optimize warehouse design, train intelligentrobot assistants, and achieve operational efficiencies. The ability to simulate and understand the performance of warehouses before their physical construction has been crucial in scaling Amazon's complex operations. They have successfully aggregated data from various CAD applications and visualized massive models with exceptional realism.

Microsoft's Azure digital twins is a platform that allows the development of twin graphs representing complete environments, ranging from buildings and factories to cities. These digital models offer valuable insights for improved product development, optimized operations, cost reduction, and enhanced customer experiences. An example of digital twin utilization can be seen in Rolls-Royce's management of over 13.000 commercial aircraft engines. These engines are equipped with numerous sensors that provide telemetry data on engine health, performance, fuel usage, and service requirements. To handle this vast amount of data, Rolls-Royce employs a digital twin solution built on Microsoft Azure, which enables a digital feedback loop for product updates, optimized maintenance processes, and real-time monitoring of the entire engine fleet during flights. This technology has enabled Rolls-Royce to offer its ''Power by the Hour'' service, creating a new business model that lowers costs for airline customers [26]. Kongsberg's dynamic digital twin integrates safety, rapid prototyping, and implementation, connecting offshore and onshore users in the oil and gas sector. This digital twin is based on KognifAI, an open digital ecosystem platform that provides digital twin solutions across multiple industries, including maritime, drilling, wells, and renewable energies [27].

4. Applications Across Industries

Many authors have explored the use of digital twins to uncover the benefits and challenges encountered in their development and implementation. The literature mostly focuses on reviewing existing studies on digital twins, with some works demonstrating their practical application, and fewer case studies specifically address the creation of virtual products, processes, or systems, as digital twins are referred to.

As the application of digital twins becomes increasingly certain yet challenging in various industries, exploring the areas where they can be applied proves beneficial. Most applications of digital twins are in the following industries:

1. Manufacturing: digital twins can be used to optimize production planning and recourse allocation, simulate production process, optimize industrial human-robot collaboration, monitoring and prognosis production tools, optimize warehouse management [29], monitoring of machine performance enabling early issue detection and prediction, enhances connectivity and feedback among devices, and improving reliability and performance [20]. As an example of a digital twin for process automation (autonomous driving), the simulation of automation in BMW can be highlighted [30]. Autonomous driving is a significant source of competitiveness in the automotive industry. The technical solution for autonomous driving is a highly complex task, requiring a large number of engineers working on one product, within a vast software repository, and addressing various scenarios that need to be anticipated. Engineering challenges can be optimized by leveraging digital twin simulation platforms, combining simulation with statistics and scenario analysis to overcome the extensive validation efforts required.
2. Oil and Gas Industry: According to Wanasinghe, T.,et.al. [31] the most common areas of use of digital twin in the industry are: asset monitoring and maintenance, project planning and life cycle management, drilling, offshore platforms and knowledge sharing, pipelines, marine vessels, virtual commissioning, virtual learning and training, and intelligent oilfields. An example of the use of digital twins for offshore installations, given by Sentient and Holis [32] shows challenges and solutions in designing digital twin for oil company. The most significant challenges that needed to be overcome were ineffective monitoring methods, lack of centralized key information, cost and time implications of transitioning to a new platform. As a solution, they developed a full digital replica of the platform containing all

the available equipment data that was intuitively navigable by a user through a web application.Digital twin increased yield, reduced unplanned downtime, improved workforce efficiency and safety, real-time monitoring, improved decision-making, and discovered additional avenues for profit-making and uplift.

3. Aerospace: Most common use case for digital twin is refer to design customization, prediction of the life of aircraft structure and assuring its structural integrity [30], optimization of the transport load [34], virtual testing or simulation. Boeing, among other companies in the aviation industry, has embraced digital twin manufacturing. By implementing the digital twin asset development model, Boeing has successfully achieved a remarkable 40% enhancement in the initial quality of parts and systems used in airplane manufacturing [35]. This is accomplished by utilizing ultra-high-fidelity simulation software, which helps to create a virtual three-dimensional model that can simulate the lifecycle of the asset, including the environments and conditions it will encounter.
4. Building and Construction: digital twin is used for evaluating space capacity and smart design, structure safety monitoring [36], virtual prototyping and verification, building management and quality control, optimizing project processes, and automated project control. One example of predictive digital twins for real-time monitoring and maintenance was used by the Norwegian Public Roads Administration, to predict damages to bridges [37]. They use IoT sensors for detection and behavior on bridges. Data is collected on the cloud, and if bridge dynamics deviate from the present thresholds system issues alerts. This reduces emergency maintenance costs, creates proactive and predictive maintenance, and rely on knowledge and data road management.
5. Medical and Healthcare – most common use for digital twins in healthcare refers to optimizing elderly healthcare services, diagnosis, and therapy, preventive treatment, drug development, medical device utilization, education and training, surgery, or medical simulation. According to Liu, Y., et.al. [38]healthcare simulation mainly focuses on healthcare education, healthcare mechanical simulation, resource allocation optimization and business process simulation, and clinical trial simulation. Barbiero, P.,et.al. [39], proposed a model of digital twin for a panoramic view of the whole body for preventive purposes. That model is based on artificial intelligence, mathematical models, and neural networks. So far, it has been tested in two clinical studies. In addition, one of the examples can be a digital twin model for detecting and predicting causes of thrombosis, based on a simulation of the flow of blood through the heart presented in the work by Shang, J. K., et.al., [40].

These are just some of the use cases in specific industries, but we can expect the development and utilization of digital twins to grow not only within industries but across the entire ecosystem. A prime example of this is the emergence of virtual cities, where digital twins can be instrumental in modeling and simulating urban environments [41,42], leading to improved planning and decision-making processes [43-56].

5. Use Case in the Elevator Industry – Schindler Company

Schindler is a global elevator and escalator company, providing solutions for vertical and horizontal transportation systems for buildings of all sizes, types and forms. It has more than 69.000 employees in 100 countries around the world. They cover the full life-cycle – from planning, sourcing/manufacturing, installation to maintenance and modernization.Schindler has been working on digital twin concepts since 2017. In the recent years it has started working on digital transformation, which is going beyond enabling the digital twin technology. The adoption of digital twin technology represents a paradigm shift in work practices, requiring significant alterations in the interaction with diverse artifacts, including documents, materials, products, and data. This transformative approach necessitates substantial modifications in associated processes throughout the entire lifecycle, encompassing activities such as development, industrialization, validation, training, and maintenance. Following initial feasibility studies, the initial productive implementation of digital twins has been achieved in the domain of escalators.

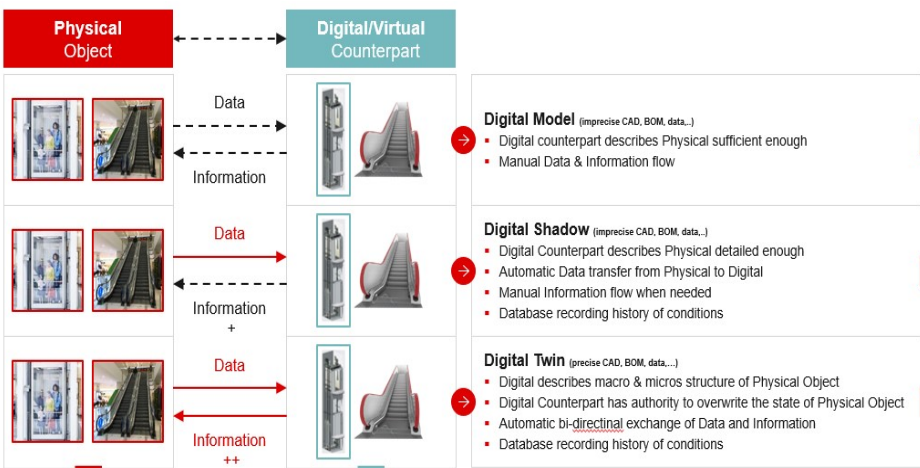

Figure 5. Physical connecting virtual; division into three categories depending on integration level by Schindler

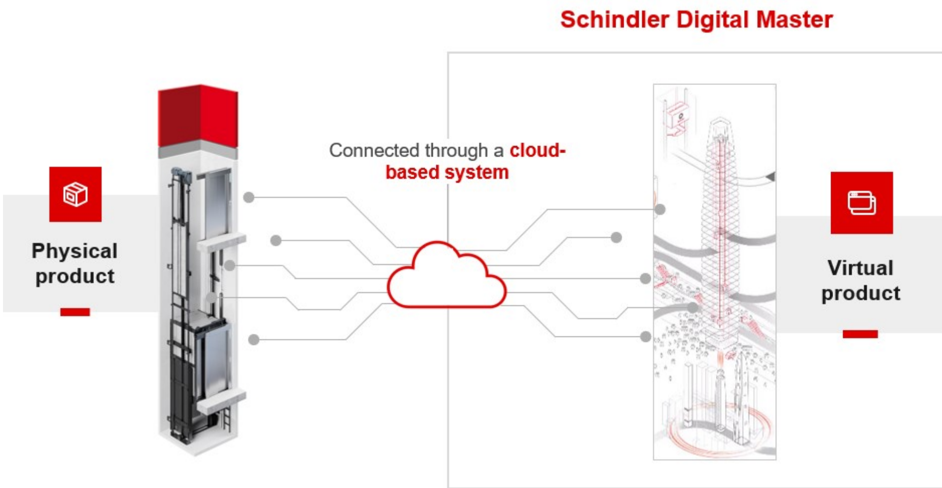

Figure 6. Digital twin of the elevator by Schindler

Leveraging the successes of this initial deployment, ongoing endeavors are underway to extend the application of digital twin technology to the elevator business.

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In Fig.7., the digital twin is described as a data-driven architecture that links together information generated from across the value chain and product lifecycle at any instance of time.
In the first phase of the product lifecycle, called requirements engineering, all product requirements are defined (such as height, number of floors, motor power, number and type of parts, material sources, etc.) based on its intended purpose (e.g., residential or commercial building, hospital, skyscraper). This is followed by the digital representation of these requirements, and then the 3D design of the configurable product, which includes both standard elements and customizable elements (e.g., stair length). Subsequently, product simulation is conducted using a 3D mathematical model, utilizing various tools and analyses such as Failure Mode and Effects Analysis (FMEA), mechanical and material analysis, oscillation, vibration, etc.
The result of this simulation is a highly detailed model for each part, ensuring product functionality. The benefit is the significant reduction of costs associated with prototype construction and testing.

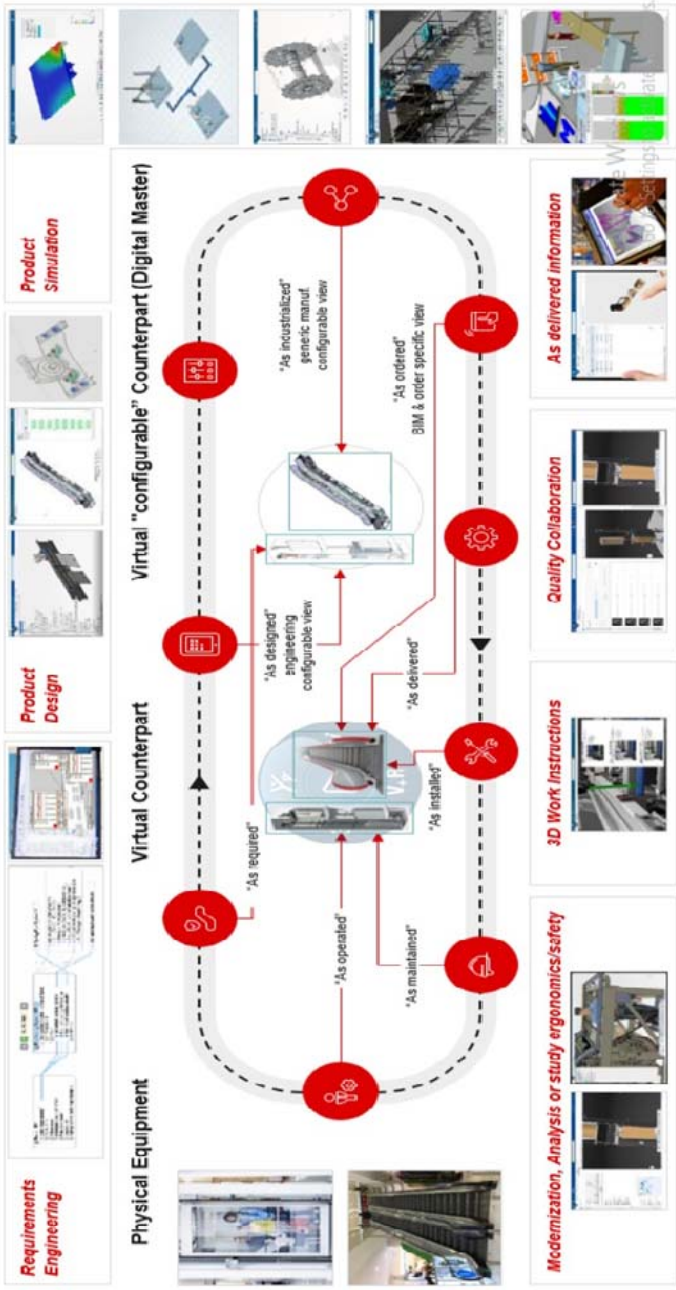

Figure 7. Digital twinlifecycle by Schindler

In the ‘’as delivered information’’ phase within the integrated system, the model or part is sent to the production machine (e.g., laser cutting machine) for manufacturing. The ‘’quality collaboration’’ phase involves virtual reality (VR) training of employees for product installation, while simplified 3D models and work instructions provide manuals for installation, maintenance, defect detection, and control (including ergonomics and malfunctions).

Through the use of IoT devices and remote monitoring, which track the functionality of the installed product and collect data for analysis, preventive maintenance is enabled.

Digital Twin technology and service providers are offering support to start with, however, in the end, for large organizations with different platforms and many legacy systems and processes, it is still their own task to go through the digital transformation.

Main challenges are (1) in transition from ‘’old’’ to new, that is in strategy and procedures to migrate and keep operational in the same way. This requires one the one hand dedicated resources, and other large investments into implementation and migration projects. Once the decisions for investments are made, the implementation challenge (2) of choosing the right partner(s) is coming on-board. Supplier base is large, but very few providers fit ‘’exactly’’ into the target business model and the industry. That means that lot of effort is to be spent to ensure good cooperation and optimal services from the chosen provider(s). The fact that the technology standards in the area are not yet established is an additional factor to be considered. Last but not the least (3), even most important is the challenge related to motivating the employees to change their way of working. The main drive for this is good and consistent communication and making sure that the change is good for everyone.

In Figure 8., the right side depicts the existing infrastructure with various applications and domains in which they are used. Integrating these applications is a key challenge in building a digital twin. The left side of the photo illustrates how product and object changes are managed prior to product manufacturing. Cloud technology serves as an enabler in constructing a digital twin due to the complexity of operations and geographical dispersion of business.

Schindler has been maintaining the data on different platforms suitable for particular parts of the value chain (e.g., one for the development of 3D models and exchange with the CNC machines and another for transaction processing the equipment tests before putting into operation or regular maintenance, etc.). With the Digital Twin approach, the need for a common platform or platform suite has increased.

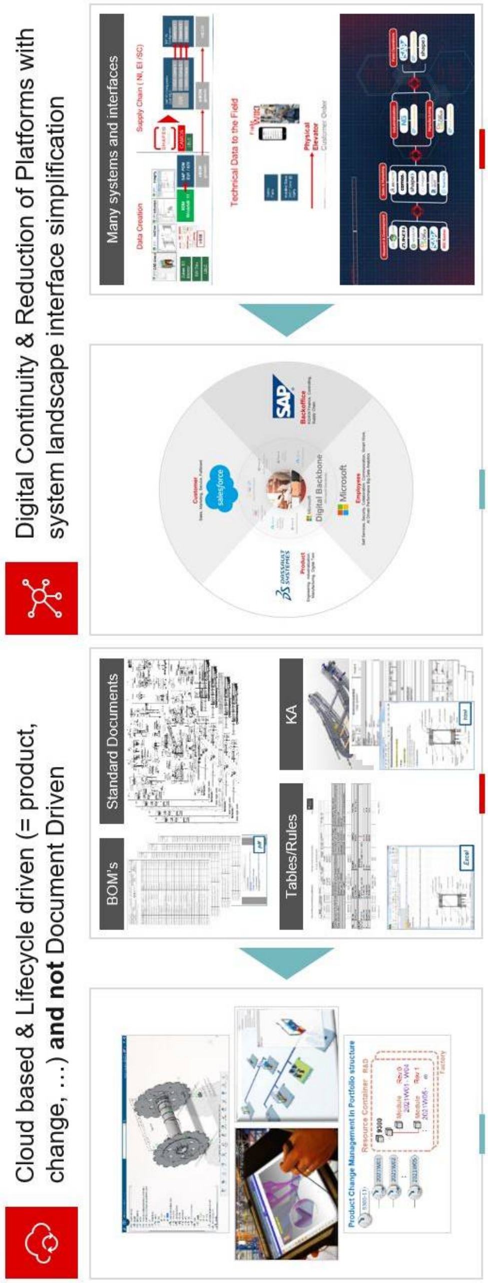

Figure 8. Cloud based product lifecycle management with digital continuity and reduction of platforms by Schindler

The vendor chosen to provide the main parts of the platform in the current phase of Digital Transformation is Dassault, a company having a background in the aeronautics industry, where from they have derived knowledge and experience in 3D & business process modeling.

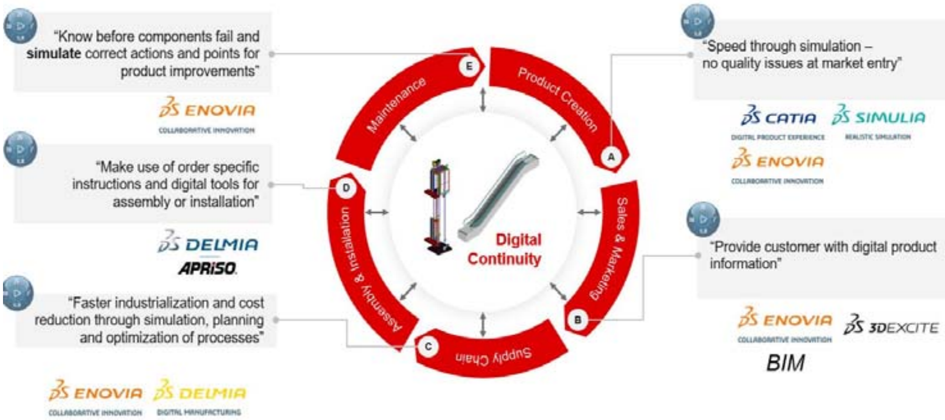

Figure 9. Digital twin platform for integration by Schindler

Digital twin provides Schindler with many opportunities to simulate not only the actual product, but also their manufacturing, installation and full operation. It provides sustainable and cost saving methodology and tools to simulate different scenarios and prevent from potential failures. Due to the built-in guidance by the implemented tool, it provides at the same time more adherence to the defined processes, as well as excellent collaboration platform for teams across different development and manufacturing sites around the world.

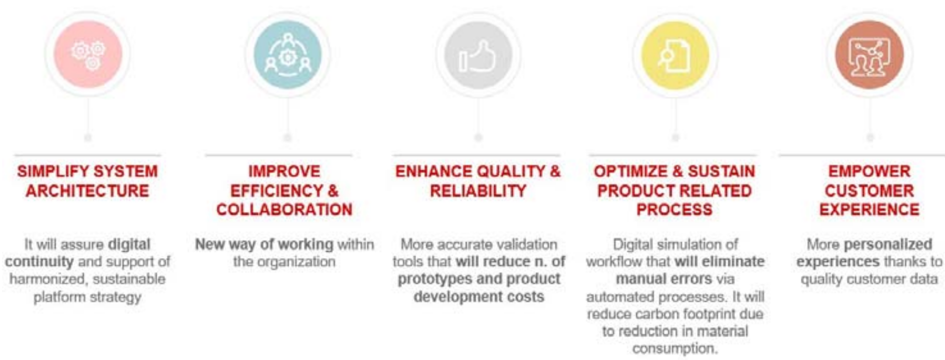

Figure 10. Digital twin benefits by Schindler

6. Conclusion

Digital twins are revolutionizing industries by providing a digital representation of physical assets and systems. As technology continues to evolve, digital twins will play a vital role in driving innovation, efficiency, and sustainability in the digital era. Embracing digital twins offers organizations a competitive edge in the digital era and opens up new possibilities for innovation and growth. Additionally, the connection between digital twins and the metaverse presents exciting opportunities for innovation. By linking multiple digital twins in a single environment, companies can build the foundation of the industrial metaverse, facilitating seamless interaction and collaboration between virtual and physical worlds.

It is expected that future research on digital twins will move in the direction of solving the key challenges identified in their implementation in organizations. First of all, the challenges in improving the integration of data and real-time analytics, by exploring the new possibilities of advanced techniques such as machine learning and artificial intelligence for real-time monitoring, as well as the use of predictive analytics. Scalability and interoperability challenges must be addressed to enable seamless integration and interaction between digital twins across different systems and organizations. Secondly, by exploring innovative human-digital twin interaction paradigms, such as augmented reality and natural language processing, thereby improving user experience and control. Thirdly, the ethical and legal issue of privacy, security and data ownership is an area that still has a lot of room for improvement. In addition, the sustainability and environmental impacts, as well as the socio-economic effects of digital twins on organizations and the workforce, require further research.

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