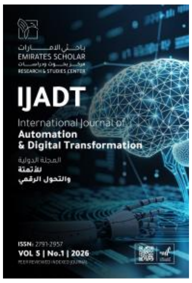

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Systems Modelling Language-Driven Digital Twins - Applications, Challenges and Sustainability: A Comprehensive Review

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ABSTRACT

Using data from various Internet of Things (IoT) sensors attached to any object, system, or process, which is integrated by a specialized model, a digital/virtual blueprint of the physical entity can be attained. Such blueprints that can mirror their real-world counterparts in real-time are known as Digital Twins (DTs). These twins heavily rely on diverse forms of data, and the ones that use the Systems Modelling Language (SysML) to streamline the same are referred to as SysML-driven Digital Twins (SysML-drivenDT's). Such model based twins are revolutionizing industrial processes such as predictive maintenance and operational optimization in plants through a structured, model-based approach to capturing and simulating complex systems. Here we show the technology behind the functioning of a DT, its vast applications and advantages in the industrial world, and ways to boost efficiency and unlock a massive potential, along with some of the limitations regarding its use. This paper explains the integration of visualization and human interaction tools such as Virtual reality(VR); how SysML-driven DT's can function in various industries, including robotization of product lines, predictive maintenance, monitoring, cost reduction, and minimization of emissions and waste, and the ways in which it is able to benefit industries, along with limitations such as high initial cost and usage difficulty due to technical complexity. In this paper we also discuss how DTs can play a major role in sustainability. The paper also goes over a case study conducted in China related to a manufacturing company and DTs. Our discussions provide a solid overall view on this technology and explains in depth the key aspects of its functioning and usage. The paper highlights that DTs can revolutionize the industrial sector, while acknowledging some of its technical constraints. It demonstrates how DTs have a major scope of implementation and how upgrades like integration with technologies like VR, artifact reuse, interoperability and a green twin model can upgrade the DT concept, making it better.

Keywords: *Digital Twins, smart manufacturing, Model-based Systems engineering, Sustainability, Circular Economy, Reconfigurable Manufacturing Systems, Model-Based Systems Engineering, Real-Time Simulation, Interoperability, Predictive maintenance*

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Introduction:

DT's are virtual replicas of the physical process of plants and systems driven by real-time data, IoT, and sensors. They are transforming and redefining the industrial system through predictive maintenance, lifecycle modeling, and operational optimization across the plant's life cycle [1]. Even though the concept of DTs has come into popularity only since the Industry 4.0 revolution, its concept can be traced all the way back to the 1990's [2]. David Gelernter in 1991 introduced a concept in which software models mimic the real world through the input of information from the physical world; he called it "Mirror Worlds". In 2002, the concept of a DT was related to product lifecycle management (PLM) by Michael Grieves in the University of Michigan and was named Mirrored Spaces model. In 2006 the name of the model proposed by Grieves was changed into "Information Mirroring Model". The term Digital Twin was first used by NASA in NASA's draft version of the technological roadmap of 2010. DT was referred to as the "virtual digital fleet leader". NASA was the first organization to define DT; they defined DT as 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". NASA also used the concept of the DT for the Apollo missions, where space vehicles were built in such a way to mirror each other. The US Air Force followed NASA's footsteps to start using DT technology for their aircraft [3]. However, Michael Grieves was the one who coined the term "Digital Twin"[4].

Modern industrial systems are extremely complex with mechanical, chemical, electrical, and fluid systems working all together in harmony[5]. For decades, industrial plants used manual, time-based, or reactive maintenance using human inspection and fixed schedules, leading to high unplanned downtime [6]. With the start of the 4th industrial revolution since 2011, a wave of digital technologies like IoT, Artificial intelligence(AI) and machine learning(ML), and DTs has become mainstream in industrial plants and processes. DTs are increasingly being used across industries [7]. A 2022 McKinsey report shows that over 44% of industrial plants have developed and implemented a factory-level DT [8]. DT-based predictive maintenance can reduce downtime by 50% and maintenance costs by 10-40% [2]. DT implementation also led to 30% energy savings, operational cost reduction, and improved maintenance strategies [9]. ML enabled DT's can also achieve high predictive precision in surface finish (>94%) and in power consumption (>98%) [10].

Although many studies provide DTs' technical aspects, only a few focus on qualitative insights such as cost reduction and energy consumption. Furthermore, areas such as SysML integration, artifact reuse, interoperability, and sustainability through DTs remain underutilized and further need to be studied in industry-wide analysis[11].

DTs integrated with Model-Based Systems Engineering (MBSE) build on systems engineering principles while emphasizing modeling as a central activity. Using modeling languages like SysML, DTs represent systems through functional and structural views specific to the asset.[12] TheseSysML-driven DT's manage large volumes of data to enhance predictive maintenance in complex manufacturing systems.

Effective lifecycle management is central to DT execution, with artifact reuse being a key aspect. The four foundational pillars that enable effective reuse are: modular architectures supporting component updates, standardized interfaces ensuring compatibility, rigorous version control, and blockchain technology. The healthcare sector, for instance, utilizes blockchain's data for provenance requirements.[13] DTs at present may also start to struggle in visualizing modern systems which is where 3D and VR may offer significant advantages. With improved comprehension and better visuals, the future of DT lies in 3D visualization.[14].

Sometimes, DTs extend beyond products to more complex systems like supply chains, emphasizing the growing need for interoperability. Mature DT ecosystems ensure real-time collaboration among interconnected DTs to increase overall efficiency, especially in systems such as supply chains. DT interoperability along with a proper DT ecosystem is important to understand the interplay of such interconnected systems.[15] The applications of DTs for increasing production efficiency and energy consumption in different sectors is discussed. DTs are leveraged in smart manufacturing for automation of production lines, maintenance, repair and operations (MRO) and plant wide process monitoring.[16][17] In the aerospace and automotive industry, DTs aid in improving the product design prior to its deployment in the real world, and hence aid in optimization beforehand. The DT of a vehicle can help improve safety parameters by virtually testing it across diverse environments.[18] DTs enable data-driven decision making by integrating IoT sensor data for real time monitoring and AI based analysis to predict the city behaviour by identifying emerging patterns in smart cities. DTs assist in effective energy and infrastructure management thereby promoting sustainability.[19]

The recent work that has been done using DTs is Destination Earth (DestinE): European Union[20] and Smart Cities & Infrastructure[21]: Singapore's Virtual Singapore. There are some key areas where improvements are needed in DTs: improvement of real-time Data Integration, many DTs still struggle with data latency, incomplete data streams, or inconsistent updates[22], Mature Interoperability, lack of standardized interfaces across the cross-domain and multi-vendor DTs hard to implement[23], Lifecycle Management & Reuse, Rebuilding models from scratch is a time-consuming process and costly[24]. Enhanced Visualization with VR, Complex models cannot be effectively used if they are too hard to interpret[14][25]. Stronger Predictive & Autonomous Capabilities, many current DTs are descriptive or diagnostic, but lack predictive intelligence[23]. Sustainability & Energy Efficiency, Industries want DTs that support ESG(Environmental, Social, and Governance) goals[26][27], Robust Security & Privacy, DTs rely heavily on sensitive sensor and operational data[28]. The main problem is ensuring reliable, cost-effective, and sustainable operation of complex industrial plants by reducing equipment failures and optimizing maintenance and production planning. This research fills the gap by providing a SysML-driven DT framework that improves predictive maintenance, operational efficiency, and sustainability in complex industrial plants, while addressing challenges in real-time data integration, interoperability, lifecycle reuse, and secure visualization.

1. Review-methodology

2.1: Literature search and selection methodology

The literature used in this review was systematically collected, screened and reviewed before selecting from established academic databases to ensure the credibility and quality of the selected literature. The major databases that were used included Google scholar, PubMed, SpringerLink, and ScienceDirect, as these databases contain a broad access to articles related to sustainability, DT's and systems engineering.

The research strategy adopted has been aimed at identifying relevant articles related to SysML-driven DT's, as well as their use, specifically within the manufacturing systems, sustainability, etc. The relevant articles have been identified using keywords such as 'manufacturing systems and digital twins', 'VR in digital twins', 'VR adoption in digital twins', 'Applications of Digital Twins in Manufacturing sectors', 'Digital Twins and sustainability', 'Model based systems engineering', and 'SysML-driven DT's' on the

databases. In order to be relevant with technological advancements, articles within the range of 2012 - 2024 have been considered. The literatures used though were mainly after 2020 to make them even more relevant. This time range was used as it helps us capture the changes in DT technology and its rapid development while ensuring that the review remains aligned with current industrial trends and practices.
Once the literature was selected, the abstracts of the literature were read through to narrow down the main ideas of the text. Any abstracts that included a majority of main ideas not relevant to our research question were rejected. Peer reviewed articles were only chosen that were explicitly related to DT's, SysML or model based systems engineering focusing on industries, manufacturing sectors and sustainability. Studies that were not peer reviewed or did not directly address DT's and their applications or integration with systems engineering and sustainability were rejected.

We had initially selected more than 80 articles from academic databases, which after going through multiple screening stages, reduced to around 40 research articles. Our team followed the PRISMA technique (Preferred Reporting Items for Systematic Reviews and Meta Analyses) and its 27 step checklist to ensure transparency and reproducibility. The PRISMA framework was applied systematically to articles identification, screening and in the inclusion and exclusion of the articles initially identified. The remaining papers formed the basis for this paper.

2.2: Foundations of SysML and Digital Twin Technology

.2.1: Core Principles of SysML and Digital Twin Technology

The SysML, derived from the Unified Modeling Language, is used to analyze and design complex systems. In order to make accurate estimations, many different types of data and the relationships of the simulation model are required. The SysML system model offers the possibility to represent data in a consistent and linked way. Thus, diverse data can be stored in an available and demand-oriented way [29].

System models such as SysML serve three main purposes for their use and application. Improving communication, documentation of system architectures, and analysis of the system towards the chosen system architecture [30]. SysML is able to achieve this through Block Definition Diagrams (BDDs). The system structure is represented by BDDs and internal block diagrams (IBDs). A BDD describes the system hierarchy and system/component classifications. The IBD describes the internal structure of a system in terms of its parts, ports, and connectors. The package diagram is used to organize the model [31].

DTs are a fusion of multiple simulations that map the behavior of a physical system in the digital space [22]. The original motivation for using a DT is the virtual validation, prediction and optimization of a mechanical system throughout the entire product lifecycle without affecting the actual use phase [32]. These simulations utilize the best available models in combination with sensor and historical data to create a digital extension of the system.

DTs can be employed at different levels of the manufacturing system. At the factory level, DTs supervise the physical properties and features of the manufacturing system, including energy consumption, error rates, and maintenance. At the machine level, DTs have been applied to monitor machine tools, components, and measuring instruments. At the process level, DTs can be used to supervise manufacturing technologies such as milling, polishing, and drilling [22].

DT data structures mainly consist of physical entity data, virtual model data, service-related data, and domain-based knowledge. For the proper functioning of a DT, the following steps must take place. Firstly, data collection and storage, which involves Physical entity data, virtual model data, and service data from different application objects, situations, and scenarios that need to be unified and then stored. The process of unification is carried out by the SysML model. SysML provides formal definitions and structural clarity. This makes it possible to link sensor data, simulation results, and operational parameters across the lifecycle of the system. This is followed by data association and fusion, data sorting, and data coordination [33].

Furthermore, MBSE builds on systems engineering principles while emphasizing modeling as a central part of the engineering process. By using modeling languages like SysML, it allows systems to be described through multiple views, such as functional, behavioral, or structural, specific to the stakeholder [12].

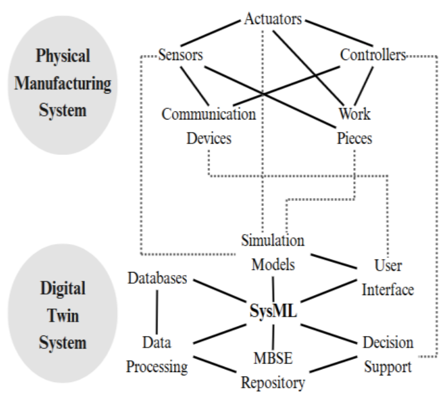


Figure 1: Cyber-Physical Manufacturing Loop. This figure explains how a Physical Manufacturing System (PMS) and a Digital Twin System (DTS) interact. The loop highlights the bidirectional data flow between PMS and DTS, illustrating the unifying role of SysML between sensor data, simulation, and models across the systems lifecycle to enable predictive maintenance and optimisation.

2.2.2: Enabling Real-Time Simulation and Operational Optimization

Real-time simulation and operational optimization of Reconfigurable Manufacturing Systems (RMSs) is enabled through the integration of hybrid modelling and SysML-driven DT engineering. In such systems, the transfer of data in the DT architecture is autonomous, in real time and bidirectional [22]. This means that DTs can support real-time simulation by continuously syncing virtual and physical systems. Such hybrid models combine the existing knowledge used in physics-based models to simulate certain phenomena of manufacturing systems with the ability of data-driven models to handle large amounts of data and are thus employed to enhance predictive and diagnostic capabilities.

An Artificial Neural Network (ANN) is a computational model inspired by the functioning of the human brain, designed to analyze data, learn complex patterns, and identify intricate relationships within these data. Information flows through the ANN from the input layer, where it receives external data from sensors and other input variables, to the output layer which provides a prediction or decision. In addition, hidden layers, which can vary in number and size, are responsible for extracting and learning complex patterns and behaviors as a function of the input data [34]. Additionally, an ANN can be supplemented by a substitute ANN when there are input gaps during the operation of the model [22], ensuring that the DT can function even through data limitations.

Recently industries highlighted the growing convergence of artifact reuse and interoperability strategies. For example, cross-domain DTs in smart cities now use standardized reuse protocols with interoperability structures to work with infrastructure monitoring. This approach helps both technical efficiency (through reuse) and ecosystem integration (through interoperability) which creates a full lifecycle management paradigm. This convergence will define next-generation DT architectures. [24][35]

2.3 Lifecycle Management: Artifact Reuse

2.3.1 Influence of Artifact Reuse on the Digital Twin Lifecycle

Artifact reuse has come up as a revolutionary method in DT life cycle management, offering a lot of benefits but also unique challenges. There are three foundational pillars that enable effective reuse: modular architectures (supporting independent component updates), standardized interfaces (ensuring compatibility), and rigorous version control (maintaining traceability). These principles are more important in complex systems where multiple stakeholders interact with shared DT parts. [24]

Manufacturing case studies show 30 to 45% reduction in development time when reusing appropriate simulation models and data structures. The aerospace sector shows even larger results, with one implementation reaching 60% faster deployment with proper component recycling. However, these benefits also come with limitations to consider. Unmodified reuse often leads to a gap in performance of about 15-20% due to mismatches. This emphasizes the need for proper adaptation when reusing artifacts [36]

Blockchain is a game changing technology for artifact reuse management. Smart contracts automate about 85% of verification processes for reused components, while the unchangeable record system reduces the audit preparation time by 70%. The healthcare sector applications also show blockchain's value in keeping data provenance requirements. However a 15-20% performance expense has been noticed that may reduce real time applications.[13]

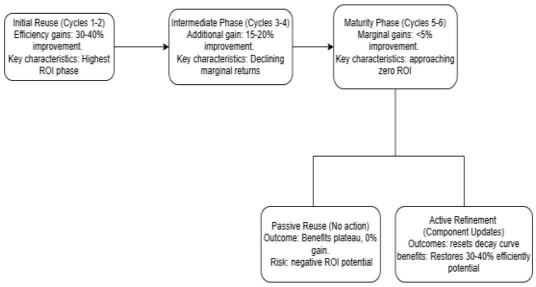
Implementation considerations are:

Version control systems must support both linear and parallel development branches [24]

- Metadata tagging methods should hold both technical and contextual parameters [36]
- Blockchain implementations require careful architecture selection (permissioned vs. permissionless) based on use requirements [13]

1. Scalability Considerations: The automotive case study emphasizes that artifact reuse scales non-linearly—while initial reuse gives 30-40% efficiency gains, the marginal benefits lessen more than 5-6 reuse cycles unless components are actively improved upon. This suggests the need for improvement protocols alongside reuse strategies. [36]
2. Domain-Specific Adaptations: Healthcare DTs need stricter reuse leadership than manufacturing systems due to regulatory issues.[13] Here, blockchain's tamper-proof tracking adds compliance assurance but requires 15-20% more storage capacity.
3. Emerging Tools: AI-powered metadata tagging now automates 60-70% of artifact categorization work, solving a key issue in large-scale reuse initiatives.
4. AI-Augmented Reuse: Recent advancements in ML are changing artifact discovery. AI-assisted matching algorithms can now identify probable reuse areas with 89% accuracy, compared to the 60% with manual methods. This is very important for large organizations managing thousands of DT components. [35]
5. Lifecycle-Aware Versioning: The latest findings show the need for "temporal versioning" that considers a component's time in its lifecycle. Components at the end-of-life require different reuse considerations than newly developed ones, changing both performance expectations and maintenance requirements. [24]The financial implications of artifact reuse are becoming clearer. The expanded analysis of 47 enterprises shows that organizations

with stabilized reuse programs consist of 18-22% lower total cost of ownership for their digital twin ecosystems. This contains savings in development, maintenance, and decommissioning phases.



Flowchart 1: Non-linear scalability of artifact reuse benefits showing efficiency gains decline after 5-6 cycles without active component refinement. This pattern highlights the need for lifecycle, continuous improvement in order to sustain long-term benefits

2.4 visualization and human interaction: VR tools

2.4.1 The integration of VR in SysML

SysML remains underutilized in industry, often due to management and stakeholders preferring the data output to be presented in generic documents (Microsoft Word/Excel formats). This results mainly from unfamiliarity with SysML. To address this issue, the Cameo Systems Modeler (CSM), a software tool used for creating, analyzing, and visualizing SysML models, was used. CSM contains the Cameo simulation toolkit, able to support a multitude of scripting languages, which is why it was used. Unity was used as the 3D simulator, as it allowed the automation of creating and managing 3D components representing elements of a real-life model. Communication between Unity, SysML models, and generic documents was established. This allowed for synchronization between the SysML model and Unity and automatic development of the 3D elements in Unity and analysis of the model by Unity and SysML. This was done by a two-way communication method where the SysML model's data was automatically exported to Unity in formats it can read, such as Excel, and then Unity creates and updates the 3D model. Then the user interaction data is exported via Excel and imported into CSM which analyzes the results, ensuring requirements were met, that the model behaves as expected, and whether the output was valid. A seamless workflow was created by using Velocity Template Language (VTL) which extracted data from the SysML into generic documents and MATrix LABoratory(MATLAB), a software used to perform numerical analysis, computing, and simulation of the physics of the model. MATLAB was used to send and receive those numeric values and data with Unity and the SysML models, enabling accurate behavior of the simulation. [14] [25]

2.4.2 Converting a traditional 2D SysML into a 3D model

With newer developments, MBSE needs to ensure that systems are properly and more efficiently visualized as 3D models rather than 2D models. Conversion from a 2D SysML created and stored in an IBM Rational Rhapsody into a 3D model in Unity required three essential steps:

A) Relevant data to be extracted from the SysML model, mainly the connections between high-level elements. This data was extracted from a Computer-Aided Software Engineering (CASE) tool database, which allows for real-time simulation, with a live connection between the model and the CASE tool database. If a live connection is not available, then an offline file containing the model data can be used, although it will lack real-time simulation,

B) Establishing communication between the data and the 3D model. This can be done through a passive communication model, rather than an active model, which requires a live connection. Through the communication, data was transferred to the 3D model,

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C) Processing the transferred data by directing the data through an abstract variation of Nodes (identifiers), Paths (connections between Nodes), and Diagrams (collections of Nodes and Paths), in order to structure the data efficiently.

Through this, information is transferred between teams and projects and this simplifies the presentation of increasingly complex systems. [37]

2.4.3 Creation of 3D VR visual

By using a variety of diagram types for graphical representation, various aspects of a system model can be modeled, such as:

- Requirements of the system by using requirement diagrams

- hierarchy in the system's architecture among the subsystem blocks via BDDs,

- communication pathways within the system, visualised through IBDs.

These diagram types were structured in a "ground-based telescope system model" which is able to use all the SysML diagram types working together to provide a coherent representation of the system.

Through the integration of Unity 3D into CSM and the use of the diagram types a 3D visual was created which, after connecting a wireless Meta Quest VR headset, was able to be visualized. The model had layered the 3D structure allowing each component to be seen separately by highlighting that component. The user could then enlarge the model and navigate to different components, providing a much simpler and more intuitive model compared to a 2D version.

The effectiveness of VR representation of a SysML model was evaluated using 2 groups of individuals, each consisting of 14 people. One group was exposed to a 2D model on the CSM 2024x, and the other to the developed 3D model. Each group was asked 15 standardized questions in order to evaluate how understandable the model was, how well information could be shared from the model, and how it assisted with language training. In the second test, 30 individuals were exposed to both the 2D and 3D model and then were surveyed on the benefits and drawbacks of the 3D model compared to the 2D model. This two-part test was done to prevent any bias that may arise when exposed to both models. [38] [39]

2.5: Interoperability in DT's.

DTs are no longer limited to manufacturing or products, but encompass entire cities, supply chains, or dynamic systems, such as ports [40][41]. As a result, DT solutions from different application domains increasingly differ in terms of complexity, requirements, and architecture. This makes a general domain-independent characterization and definition of DTs increasingly challenging [42]. The maturity of individual systems in isolation contradicts new research outlining that DTs should be linked as a large whole to improve the performance of whole systems and beyond [43]. DT maturity assessment aims to evaluate the development stage of a Digital Twin , regardless of the domain, as well as the potential of a system's DT to jointly co-operate with other related systems' twinning solutions, toward a system of (twinned) systems(SoS). Interoperability is a mutual collaboration of peer DT systems, toward a joint SoS goal, rather than the exchange of needed data across DTs' modules toward achieving a single system's goal. Interoperability is discussed at the highest level of maturity in the context of supply chains, which are recognized as a SoS [44]. The importance of DT interoperability, together with the vision of building a DT ecosystem [15]. Connected DTs can therefore be regarded as tools used to understand the complexity and interplay of interconnected systems.

There are six levels in the digital twin maturity:

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1) Replication of assets, which makes a DT replica of the physical asset and shows the asset's state and structure at a specific time

2) Connections of modals and systems, the replica now includes process models that analyze historical data to simulate what happens under different conditions

3) Synchronization of data and processes, real-time data is integrated via sensors and IoT, which helps live synchronization between the physical and digital versions.

4) Interaction between DT and the asset, a two-way communication system between DT and the real world, and DT can send commands or controls to the physical system

5) Automation of processes, where DT acts autonomously using data and ML, which makes operational and maintenance decisions automatically

6) Interoperability across DTs, where DTs from different systems work together, which helps DTs to make joint decisions among DTs in a system of systems

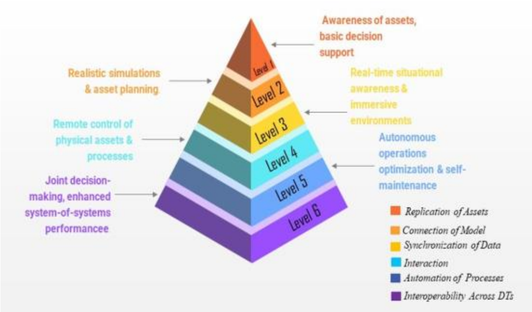

Figure 2: 6 levels of Digital Twins' Maturity: The Need for Interoperability highlighting the progression from basic decision support to full interoperability with joint decision making across multiple models and systems. The figure illustrates how sustainably optimised decisions are only possible at higher maturity levels.

In the port DT's, the fusion of data from operators, equipment, and the environment into the virtual space of a DT-based system. Thus, there is an urgent need for achieving the 6th level, enabling the interoperability of different DTs with that of the port.

In the urban DTs, the lack of interoperability between the different DTs composing the urban DT is identified as the biggest issue in the current development of DTs in urban areas[45]. Therefore, in order to enable interaction between the DTs representing different aspects of the urban environment and to efficiently optimize the various smart city processes in a SoS manner, a high degree of interoperability is required for level six.

In the Digital Supply Chain Twin Maturity, the integration of multiple DTs to optimize the supply chain, which is itself composed of multiple systems as a whole. For such a composition of different DTs that are integrated into the

In the digital twinning process of the entire supply chain, it is vital that each twin provides a high level of interoperability and thus reaches maturity level 6.

Despite the numerous benefits DTs offer to their respective actors, a lack of trust is one of the biggest barriers to their adoption and maturation [41]. This lack of trust encompasses both difficulties in setting realistic expectations and trust toward DTs [46], but also toward other related actors, as sharing data is often perceived with a loss of competitive advantages [47]. A major contribution facilitating data exchange and usage is the Findable, accessible, interoperable, and reusable (FAIR) principles [48], according to which data should be FAIR throughout the data lifecycle, which are intended to serve as a guide for those seeking to improve the capacity of computational systems to find, access, interoperate, and reuse data with none or minimal human intervention [49]. A trust framework can help to create a common understanding and expectation among actors on how data will be shared, used, protected, and governed. "A European Strategy for data" [50] is a policy initiative to create a single market for data within the EU, which includes the Data Governance Act that can be considered a trust framework for data in the EU.

The solutions and initiatives to tackle interoperability challenges are :

1) The ISO 23247 DT framework for manufacturing [51].
2) The UK's information management framework for seamless data exchange within the national DT, an ecosystem of connected DTs [52].
3) The ongoing work of the European Telecommunications, The Standards Institute, which aims to develop requirements and guidelines for horizontal, cross-cutting interoperability and the standards framework for DTs.

2.5.1 SysML-Driven Interoperability and Standards Gaps

A key gap identified in the reviewed literature is the lack of clarity on how SysML artifacts interface with simulation platforms, IoT systems, and data pipelines. While many studies show that interoperability is central to expandable Digital Twin implementations, most implementations rely on case-specific or proprietary tool integrations rather than standardized data exchange mechanisms.

SysML offers a shared modelling vocabulary through Block Definition Diagrams (BDD), Internal Block Diagrams (IBD), activity diagrams, and parametric models that can serve as a semantic backbone for DT's. However, the studies reviewed show that SysML models rarely connect smoothly with execution environments. Transformations from SysML behavioural or parametric models to simulation tools such as Modelica, Simulink, or FMI/FMU-based co-simulation engines are often manual and inconsistent across tools. This limits automatic synchronization between the designed system model and real-time simulation updates.

Interoperability challenges are more prominent when integrating SysML with IoT platforms. Most IoT systems operate using heterogeneous protocols such as MQTT, OPC-UA, REST APIs, and custom JSON schemas, whereas SysML tools lack native support for these formats, where execution is handled by external tools. The heterogeneous protocols used for operational support are often tool-specific and scrip-based resulting in limited SysML semiology. As a result, runtime data ingestion, sensor-to-model bindings, and live parameter updates require handcrafted scripts and are rarely reusable across domains[68][69].

While FAIR principles the ISO23247 provide frameworks for data exchange on an architectural level, they provide limited instructions on how to maintain SysML semiology across multiple simulations and analytics layers, leaving a crucial standardisation gap at the model-to-model runtime boundary.[70]

The absence of OSLC-based model sharing and standardized SysML conceptual models also weakens cross-tool and cross-lifecycle data flow and constrains system-to-system interoperability. The DT's models developed for manufacturing very rarely transfer over to the energy, mobility, or urban systems without the need to extensively re-engineer the models. This, in turn, directly affects scalability and long-term sustainability assessments.

Without robust interoperability, lifecycle data related to energy usage, machine health, and resource consumption cannot propagate consistently across engineering, simulation, and operational layers. This creates fragmented datasets, duplicated modelling effort, and incomplete feedback loops, ultimately restricting the ability of DT's to support system-level sustainability evaluation.

2.6 Applications of SysML-driven DT's in Various Industries
2.6.1 DT's in The Manufacturing Sector:

1. Automation of production lines: One of the most developed directions in manufacturing, especially with respect to industry 4.0 is the automatization and robotization of production lines, DTs are playing a significant role in this integration as robots are being programmed mainly by the following three methods: (i) a dedicated offline virtual environment for programming each aspect of the robotic cell for later deployment through the network to the physical robot; (ii) an online virtual environment, which is being adapted by means of sensor information, usually being twinned in the dedicated virtual environment like the Robot Operating System(ROS), and is able to directly affect the pre-programmed path and routine of the robotic systems; (iii) A manual method of robot programming with the use of a flex pendant along with the introduction of VR and Augmented Reality (AR) interfaces. It also uses a DT for manipulation near the virtual robot remotely. Moreover, DT is also used as a validation tool for Human-Robot Collaboration to test the safety level of the system first before experimenting with real operators in the actual system.[16]

2. Predictive Maintenance and Maintenance, Repair, Operations (MRO): Using different modeling techniques like simulation-based, data-based or mathematical modeling, the DT model can be utilized in the prediction of the future behavior of the assets and impacts due to disruptions. Therefore, as a living model that provides real time monitoring of the physical twin, DT is able to identify potential problems with its real physical twin. This can allow the prediction of the remaining useful life of the physical twin combining physics-based models with data-driven analytics. Thus, using continuously acquired data from physical sensors with the IoT, DT is able to deliver accurate forecasting for predictive maintenance. Therefore, DT can play a great role in early warning, prediction of life cycle of assets, and optimization of a manufacturing system through real time monitoring of the activities of a physical twin. In this area, the application of the DT model has become significant because many industries are moving from reactive to proactive maintenance to reduce operational downtime, maintenance costs, and capital investment[53]. Based on the prediction for health condition, remaining life, and faults, proactive maintenance is carried out to avoid the sudden downtime. Furthermore, when a fault occurs, with the ultra-high-fidelity virtual model of the product, the fault would be visually diagnosed and analyzed, so that the position of faulty part and the root cause of fault are displayed to users and servicemen. Thereby, the MRO strategies using DT (e.g., disassembly sequence, spare parts) are developed to recover the product[54].

3. Plant-Wide Process Monitoring: The task of process monitoring is to detect abnormalities in the industrial processes and identify malfunctions and external attacks in the machines and connected systems. With the aid of DT, the information in the actual organizational structure can be retained, which greatly contributes to the accuracy of fault localization and the interpretability of the fault propagation paths. On top of the DT network, a performance evaluation network can be built, where each node is constantly interacting with the corresponding DT to acquire real-time performance-related information. Based on such a network, plant-wide performance degradation analysis becomes feasible. The use of DT can help improve the security by providing a unique identification (UID) to each DT. This makes the information source verifiable and traceable. It reduces the risk of security breaches against unauthorized devices like external sensors and unknown data sources. In this sense, security-related services are needed in the plant-wide monitoring system.

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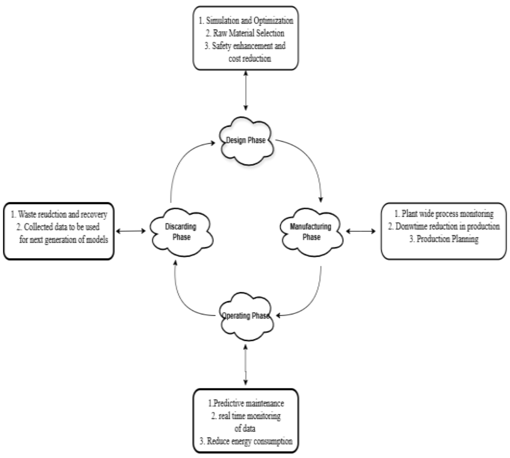
For the DT-powered services, the attractive aspect lies in the fact that the companies do not have to bother developing dedicated software and solutions for various online analysis needs. They just need to turn to the market of third-party service providers and instruct the DTs to 'use the apps'. Companies can use the DT technology without developing their own dedicated softwares for monitoring approaches. Among them, deep learning-based approaches have been rapidly developed over these years, which are likely to be adopted for plant-wide process monitoring using the massive data generated in the DT framework.[17]

4. Cutting Tool efficiency: By creating virtual counterparts for these tools, precise data can be captured throughout the production lifecycle, allowing for detailed analysis, optimized process planning, and continuous improvement. DT-driven data frameworks provide unique insights into tool wear, which is crucial for maintaining the efficiency and quality of manufacturing processes[55]. This is largely facilitated through the ISO 13399 which provides standardised format for making the components of cutting tools essential for creating DTs of these tools[56].



Flowchart 2: Life cycle of a product during manufacutring explained with the implementation of digital twins. The figure illustrates how the continuous data exchange between different phases supports circular economy and improves operational efficiency of a product.

2.6.2 DT's in The Aerospace Industry:

1. Safety and Cost cutting:One of the main purposes of DT in aerospace is to reduce the weight of the aircraft as future aircrafts need to work in more complex conditions and mirror the life of the flying twin to enable safety and reliability. One of the DT frameworks in aerospace is given the name Airframe DT (ADT) which is aimed at Operation and Maintenance(OM). After receiving the fleet data about the trajectories and diverse missions of the aircraft, which contains information about motion of the vehicle, a Computational Fluid Dynamic model calculates the aerodynamic loads applied to the airplane. These loads are subsequently transmitted to a Finite Element Model that computes the response of the aircraft, such as the vibration and stress/strain responses. The resulting damage is used as data for Remaining Useful life evaluation. To sense the change in external environment and validate the DT model, sensitive technologies like the Ni-Ti sensory particle are put into the aircraft model which can sense even microcracks and replicate the specimen. Also, the DT model can be employed as a virtual sensor to simultaneously monitor the condition of an airplane and reduce the frequency and cost of repair and maintenance.[18]

2. Enabler of New Product Development (NPD) evolution: DTs in NPD further improve the flexibility and efficiency while reducing the overall cost and period of the NPD process. Since when Boeing first employed CAD/CAE/CAM in its Boeing-777 NPD process, the aerospace NPD has undergone an evolution from traditional drawing and machine-dominated platforms to digitalization. DTs can be seen as the upgraded integration of CAD, CAE and CAM in the NPD process. DTs have proven their effectiveness in many applications such as, aircraft engine design, CNC and robot arm aided machine process and final assembly . Moreover, by virtue of DTs' information integration and high-fidelity simulation

characteristics, digital factory twins are also on the R&D agenda. The factory twin not only dynamically simulates the factory layout, production line and track job progress, but also provides market analysis and demand prediction, supply chain management, thereby bridging the management system to the production system dynamically.

DTs can improve the product quality from the initial product cycle and accelerate decision-making by high-fidelity presentation of valuable data to the customer. DTs can benefit and improve the NPD cycle in the virtual space through constant data iterations, thereby optimising and verifying the previous stages. DTs can effectively reduce the NPD cycle by 10%-75%. DTs al1. allow the originally expensive and time-consuming physical tests (e.g. material test, wind test, flight test) to move to the virtual space. The application of DTs has reduced the time originally spent on aerospace material testing and verification by 80% and 25% respectively[57].

3. Retrofitting of Aircrafts in Civil Aviation: An aircraft is retrofitted with a complete or partly new interior after every 7-8 years. Changed customer requirements of an airline can lead to changing an existing aircraft cabin and replacing it with a new one. The planning of the maintenance and retrofit procedures could benefit hugely if there was a DT of the specific aircraft with all needed information. Yet, effectively these processes are planned mostly based on established timescales, observations during intermediate maintenance and generic geometric information. However, after years in service and many MRO-actions the actual geometry differs from the once produced airframe in many aspects. Especially during the retrofit, this often leads to problems fitting the new cabin modules into the existing airframe because the exact geometrics of the airframe are just known the moment the aircraft is disassembled. Model-based support during development helps to process the complicated and extensive data volumes of aviation and to modify them consistently during methodical further development. On this basis, a modular product family for aircraft cabin monuments could be developed by means of a model-based approach, which takes into account different life cycle phases. The approach of using 3D-Scans to perform premature clash-analysis between the designed cabin and the specific airframe represents a good use case for DTs in civil aviation to enhance efficiency during the process[58].

2.6.3 Development of Smart Cities using DT's:

DTs have numerous applications in smart city development with anticipated benefits. The data collected from IoT sensors and embedded into central services within a city can help create state-of-the-art AI algorithms, which can be used for DT-enabled city management applications. This can result in better traffic management and reduction in congestion and carbon emissions, contributing to the development of sustainable cities. A smart city network may include buildings, roads, public services, logistics, people, and power grids, all of which can benefit from the applications of data-driven decision making using DTs.[21] DT plays a fundamental role in terms of collecting the data and helping in determining emerging patterns in the city behavior. If detailed measurements of its characteristics are recorded and analyzed, for example, the impacts of the introduction of a new "one way" road could be simulated and studied before deciding their implementation. Another aspect is the potential relationship between a smart city and DT representing large environments like whole cities. For instance, in many countries there are "twin" cities, that is, cities that have a deep tie and they strongly interact even if they may be far away. These twin cities could be related and studied in order to better determine the effects of events occurring in one city over the other one. The DT in this case can be useful for analysis at the higher level as well as for very specific relations, for example, transportation.The IoT devices, ranging from sensors to cameras and utility meters, can be strategically deployed across the cityscape to capture real-time insights on traffic , environmental, energy and infrastructure parameters. This can help provide a comprehensive panorama of the city's operational dynamics and environmental conditions. These insights can be integrated into a DT network to enable continuous monitoring and analysis. Furthermore, ensuring the security and integrity of data within smart city DT is important to safeguard against potential cyber threats and breaches.[19] The DT concept can help for a better composition and aggregation of functionalities independently of the specific application domain taken into consideration. The reason for this is related to the bottom up approach implied by the DT. Each single and simple object can be accessed by APIs and it can be composed and replicated for a particular goal into several aggregations of more complex objects. It will still be synchronized with the original and possibly with other instances of the object. This ensures a high level of composability and programmability[59].

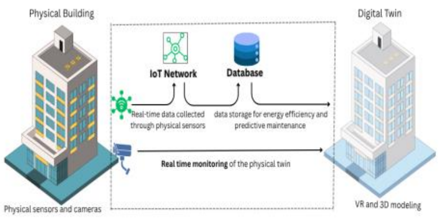


Figure 3: Application of Digital twin technology for a building for real-time monitoring and data transfer in the context of a smart city. Data is collected from sensors and transferred to a database which allows for energy consumption management and predictive maintenance allowing management of the physical building. This large-scale, continuous data exchange exemplifies the contribution of local digital twins to the broader, urban sustainability goals.

2.6.4 DT's in The Automotive Industry:

Overall Safety: Safety is a parameter of utmost importance in the automotive industry. Advanced Driver Assistance Systems (ADASs) is the terminology used to design the systems to increase the driver's, passengers', and pedestrians' safety by minimizing the number and seriousness of automotive accidents. The purpose of an ADAS is to notify users when potential impending threats are identified, to intervene when necessary in order for the user to achieve proper control of the automobile, and to prevent accidents or to reduce the severity of an accident. ADASs rely heavily on DT technology because they use multiple sensors to detect future threats. The system works in conjunction with the cloud in which all data is stored and recalled if needed. The knowledge obtained from these data may increase the ability to respond to or detect threats from existing ADAS architectures.To achieve the goal of flawless human-computer interaction while taking into account greater standards and regulations, a complex architecture is created where the DT can aid toward achieving user safety by analyzing real-time sensor data from the real-world car along with the knowledge base of the relevant protection regulation context.The American Manufacturer Tesla also uses DT technology in every vehicle they produce[60].

2. Improvement in Body in White Process: The Body in White (BIW) is a crucial component of the automotive manufacturing process, as it significantly influences the final appearance of a vehicle. The DT can be implemented into the design, pre-production, and production phases of the automotive BIW for real-time geometry assurance. In the production phase, the DT enables the development of an assembly model for the automotive body informed by inspection data scanning the components geometries for adjusting locators and clamping positions .The

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utilisation of DT technology has significantly improved welding completeness in automotive BIW panels.[61]

2.7 Sustainability and DT's

2.7.1 Sustainability and SDGs, a Brief Introduction

Natural resources available at our disposal are finite and limited and 'Sustainability' simply refers to humanity's ability to organize, maintain and support various processes including social, economic and environmental processes without totally depleting our natural resources. Sustainable development was defined by the UN in 1987 as development that meets the needs of the present without compromising the ability of future generations to meet their own needs.

The industrial revolution that started in England in the mid-18th century has a far-reaching and irreversible effect on the overall concept of sustainability [62]. The impact of the industrial revolution on pollution, trade, economy, and energy has been very strong, with both positive and negative sides. As mentioned in this paper, the industrial revolution brought in progress and poverty. The industrial revolution was the very first instance where machines started replacing man, leading to the advent of large manufacturing units replacing skilled and unskilled manual labour, resulting in massive unemployment, labour unions, strikes.

The growing assumption that natural resources are infinite has led to the shortage and overconsumption of natural resources has led to a state of disarray. Sustainable development implies a responsible consumption of resources today[63]. Leading to not only a shortage of resources but also the growing severity of climate events and change, erosion of multilateralism, and persistence of economic crises [4]. Considering these problems and in an attempt to find solutions to sustain human life on earth, in 2015 leaders in the United Nations(UN) came up with the Sustainable Development Goals (SDG's), which has evolved over the years. Today it has 17 clearly defined goals covering various socio-economic aspects and functions. The 17 SDGs were adopted to replace the 8 Millennium Development goals(MDGs) which had guided global development since 2000. The new SDGs were made to make this planet a better place and complete the remaining targets of the MDGs [4].

2.7.2 DT's and its role in Sustainability.

Section 2.6.1 focused on the foundations and technology behind DT. This section, 2.6.2, will now provide information on how DTs and its implementations can lead to sustainability and cover the limitations and challenges on the topic with a case study. This section reviews how DT's contribute to economic and environmental sustainability , outlines key mechanisms through which DT's enable sustainability and also highlights challenges and limitations to current DT - driven practices

A DT when implemented in industries can hold multiple benefits. Despite the high investment needed and also highly trained technical staff, a DT can help industries. Predictive maintenance, improved productivity and efficiency, reduced downtime and operational optimization, enhanced quality control, real time monitoring, better decision making and real time simulation of plants and systems (these contribute to the economic and environmental aspects of sustainability) are some of the benefits of implementing DT's. These benefits increase the added value of companies and also promote sustainability [64].

From the past few years, academic research has turned towards integrating sustainability and acceleration of digital technologies in what is called a twin transition. Among the most promising digital technologies is DT. DT's also support Circular Economy(CE) principles. CE represents a regenerative system, minimising energy leakage, emission, waste, and resource input by narrowing, slowing, and closing energy and material loops via design, maintenance, refurbishing, repair, remanufacturing, reuse, and recycling. CE also helps to minimize waste and promote sustainable resources by keeping products and materials in use for as long as possible. Integration of DT and CE can promote sustainability. By monitoring material flow and life cycle of plants, manufacturers can make decisions on reusability and recycling promoting the idea of a CE [27].

Since DT's enable real time monitoring it is possible to monitor the evolution of harmful greenhouse gases and optimize the production system and plant accordingly to reduce harmful gas evolution and ultimately contribute to reducing the carbon footprint [65]. DT's can also analyze, collect and process data from physical models, generating reports and estimations, this can help companies monitor pollution and emissions, create more eco-friendly solutions while also monitoring carbon footprint [27]. This real time monitoring can also help improve the energy efficiency of the plant and industry. By combining predictive analysis and real time monitoring, industries and production plants can achieve energy efficiency. DT's can also be made to include Energy Management Systems(EMS) which can be done through predictive and adaptive energy management [26].

Companies can also use DT's to virtually simulate and test production plants and lines before applying and creating them in real life. This simulation and testing does not help companies save money and also promotes sustainability as instead of needing to test the plant manually in real life by wasting resources companies can do this virtually by using the DT of the system. Instead of the test system failing in reality or the industry implementing the system with a design flaw, leading to resource wastage, the failure in the virtual model of the system will not lead to resource consumption and the manufacturers can also fix design flaws before implementing in real life in turn promoting resource conservation [66]. Paper [27] also mentions that DT based virtual prototypes can lead to 30-70% cost saving as compared to physical prototypes leading to cost efficiency for companies. Product development process also increases significantly when using DT based models in place of physical ones as DT based models allow smoother modifications, tests and optimisations as the physical environment does not limit operations. One company expressed in paper [27] that DT based motor design and optimisation helped increase their companies motor efficiency rate by 10% showing how a DT promotes sustainability while also helping a company [27].

Predictive maintenance is also one of the benefits of DT implementation that also promotes sustainability. Predictive maintenance enables early detection of operation inefficiencies preventing resource waste. Real time monitoring of the system and predictive maintenance through the DT of the plant will help identify the issue in advance, allowing the manufacturers to interfere and fix the system before resources get wasted [66].

It is even possible to fully model the potential life cycle of an industrial plant or system through the usage of DTs. This allows for the manufacturers to make data driven decisions on reusability, resource wastage and also plan for disposal at the end of life of the system. This also promotes CE[67].

DT can also help in resource optimization. Before the product production the production process can be virtually simulated allowing for productivity and efficiency analysis. Then using IoT and complex networks the supply and demand can be matched allowing for the efficient use of resources. This is called a sustainable supply chain. The DT models the entire supply chain process from production to transportation allowing manufacturers to make informed decisions reducing resource utilization. DT can also be integrated with intelligent manufacturing. Sustainable intelligent manufacturing contains sustainable intelligent manufacturing equipment, system, and service, which support each other. Once this is done manufacturers can monitor in real time, optimize energy use, make informed decisions and predict failures. Integrating DTs with IoT, AI, ML and more Industry 4.0 technologies enable this sustainable intelligent manufacturing [66].

DT's are widely implemented in the manufacturing sector and can greatly contribute towards sustainability. DT's have been identified as key technologies for contributing towards the SDG's. SDG 12 which is " Responsible Consumption and Production" in particular is greatly being contributed towards by DT's. Real time monitoring, resource optimization and energy efficiency provided by DT's all lead to SDG 12. DT's also contribute to SDG 17 which is " Partnership for the Goals through digital and global inclusivity and cooperation on DT research and advancement" [4].

This part of section 2.6.2 goes into a case study conducted in the Southern and Northern region of China. The case study was taken from previously published literature and is used as an example here to demonstrate how DT's have been applied to improve sustainability in the manufacturing sector. The case study was selected as it provides concrete quantitative evidence and conclusions of energy and cost reduction enabled by DT driven Energy Management System (EMS) in industries. The case study was about creating an EMS through big data driven DTs and then implementing them in Energy Intensive Industries(EIIs). The EMS was applied in 2 companies A and B. Company A's energy consumption went down by 3% and they saved 4% of energy costs. Now the energy consumption data can be further analysed and company A can save 5-10% of energy costs annually. Company B saw reduced environmental protection costs and they are now able to take measures to continuously save energy and reduce emissions [26], showing how DTs can lead to sustainable outcomes in real life. When implemented properly in manufacturing industries, DT can bring real outcomes in promoting sustainability. These findings from the case study reinforce the reviews observation that DT's can infact lead to sustainable changes in the manufacturing sector and industries if implemented properly.

Manufacturing companies are nowadays facing sustainability pressures. These pressures are generated from 2 places:

i) Rules and legislation - these include, Rules by NGOs and intergovernmental organizations like UN and EU, General Business rules, International agreements and guidelines like audits to obtain environmental certificates and Science-Based Target Initiatives (SBTi) with targets related to global warming.

ii) Customer and market based pressures - Many companies are being increasingly asked about Bill of materials(BoM), enhanced sustainability measures, energy efficiency and emission related matters, pushing companies to meet customer expectations and show them that they are using sustainable practices.

These pressures are pushing Companies to adopt more environment friendly strategies that promote sustainability. In order for the company to stay in business they have to be open minded and take proactive measures in order to promote sustainability [27].

Although the implementation of DT in industries can hold multiple sustainability advantages, it is not without limitations and challenges. Just creating DT's and utilising them requires vast IT infrastructure and high amounts of energy and just creating DT's leads to adverse environmental impact, working against sustainable manufacturing. Companies also face challenges when trying to implement DT's. There are many concerns over cybersecurity, privacy, data security, compatible system interfaces and IT infrastructure. Benefit - cost ratio must also be taken into consideration as the implementation of DT's requires large sums of money. Companies must also be open to new changes and skills in technology and in implementing these technologies [27]. Companies and industries also face challenges in collecting and gathering the appropriate and correct data for a DT. Energy Intensive Manufacturing Industries find it tough to collect data as data collection is difficult in harsh manufacturing conditions like high pressure, high temperature, high alkali, high acidic and smoky settings. Thus collecting data for these companies remains challenging and further research is needed on advancing DT's [26].

Manufacturing industries must also look at sustainability of their systems and process as it remains one of the most vital global issues of this generation. DT's offer significant potential for improving sustainability across the manufacturing systems, though challenges in energy use, data collection and infrastructure must be addressed. DTs are a valuable technology advancement that not only provides multiple benefits to the industry but also addresses the everlasting problem of sustainability.

3. Discussion: Challenges and implications for SysML-Driven Digital Twins

This literature review encompasses the various challenges faced and applications of SysML driven digitals twins, methods to increase their efficiency through AI, VR, and ways that DTs can ensure a sustainable future. The main bottlenecks limiting digital Twin scalability present themselves as real-time data integration, interoperability, and continuous life-cycle integration. The more uncertain limitations are the absence of standardised data transfer, verification and validation mechanisms.

As manufacturing systems grow increasingly complex, interconnected, and software-dependent, traditional document-based engineering approaches are proving insufficient. The close coordination between SysML and DT technology enables a shift from such document-based engineering to model-driven system development. It is of utmost importance for today's factories to integrate robotics, IoT sensors, and cyber-physical systems. Such an integration often needs to take place in real time, making model-driven system development essential. Through such development engineers, with the help of DTs, are able to visualize, analyze, and verify system behavior at mechanical, electrical, and software levels in a unified way. Languages like SysML provide a structured framework for capturing system requirements, design logic, and real-time feedback within a centralized model. They play a crucial role as they unify the various types of data accumulated through multiple sensors. Along with improving communication, this also reduces costly design errors and supports predictive maintenance. As manufacturing shifts toward smart, adaptive, and sustainable operations, model-driven engineering would become the foundation of the manufacturing world.

MBSE, which is enabled through SysML, contributes directly to the lifecycle integration of DTs. MBSE, by capturing system requirements and architecture, facilitates stakeholder collaboration, allowing continuity and traceability. As system complexity increases with multiple interacting physical and digital components, MBSE not only ensures consistency in design logic, but also provides a formal mechanism for linking sensor data, simulation results, and real-time feedback to evolving system models.

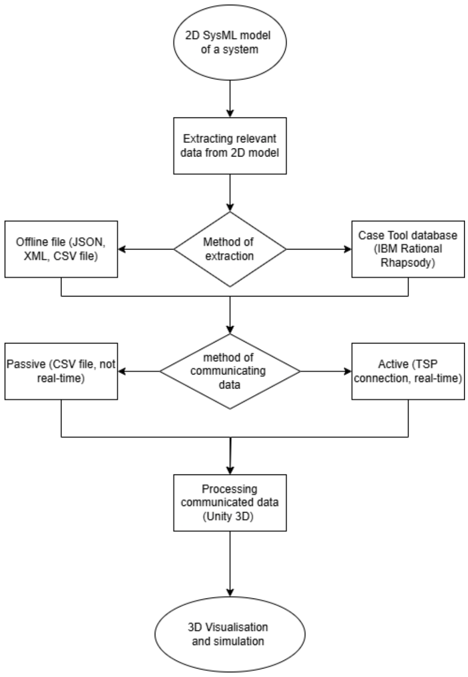
One major strength of SysML in digital twin applications is the way it is able to support reconfigurable manufacturing systems, where the ability to reconfigure hardware and software components with minimal downtime is essential. Here, SysML diagrams (like BDDs and IBDs) can be used to simulate different architectural scenarios. When DTs are integrated with these models, engineers are able to virtually prototype changes, such as re-routing conveyors or swapping robotic arms, before committing to physical changes. This reduces trial-and-error and contributes to operational optimization.

The study shows that artifact reuse is pivotal as a strategy for improving DT lifecycle management. The evidence supports that a framework made on modular architecture, standardized interfaces and rigorous version control gives a strong foundation for scalable DT deployment.

There are also a few challenges to consider - Firstly we need to consider domain specific needs, mostly in regulated industries such as healthcare, bringing unavoidable storage overheads that affect storage and processing efficiency. Secondly, reliance on supporting technologies like AI matching and blockchain verification (with inherent latency) may cage real-time applications. There is a critical balance between accelerated deployment through reuse and need for current governance to maintain system integrity is necessary.

Traditionally, SysML modeling has been represented on a two-dimensional plane, which can limit user interaction and understanding as systems grow much more complex. This increasing complexity makes it difficult to model the systems comprehensively in 2D. With these systems containing much more information which must be clearly communicated to prevent potential errors due to misunderstanding. It is for this reason that a 3D model is believed to improve comprehension by providing an immersive environment.

A 3D SysML model can either be displayed on a 2D flat screen or by introducing the individual inside the environment using VR. However, the model viewed on a screen lacks immersion of the different components, depth of field, and user interaction. While some studies have attempted to create a 3D visual from a 2D model, their focus was directed towards technical feasibility and data transferring rather than fully implementing the data in the best 3D visual they could. This limitation does prevent a full immersion of a real-time accurate visual and reduces some of the benefits described earlier.



Flowchart 3: creating a 3D model using data from a 2D model. Data is extracted from a 2D model via two methods and then communicated to the 3D model through an active or passive method. This data is then read by Unity 3D and processed into a 3D model.

VR can offer a significantly more intuitive system and user-friendly user interface. 3D models also provide a much clearer transfer of information. With the ability to immerse the user within the environment, enabling the user to more closely examine and study different components, VR can revolutionize SysML modeling, though with its drawbacks. VR headsets are often cumbersome and require some level of technological proficiency, which may be hindering engineers' ability to implement them for their stakeholders and projects. Such technology may cause sickness, nausea, headaches, and

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may even hurt the posture of its users if used for an extended period of time.

Though valid, these concerns are becoming less severe as newer VR headsets are lighter and even the adoption of augmented reality (AR) glasses promise realistic alternatives to the issues highlighted with VR [38].

DTs are being rendered the most by the manufacturing sector to make the production process smoother and cost effective. DTs utilize IoT sensor data for real-time monitoring of a product's lifecycle. In smart manufacturing,a DT can very well be used to create a live virtual world of a factory or even a production line which can be tested under different conditions. DTs aid in reducing energy consumption as they don't require physical testing and cut costs to a large extent. DT technology can be used to test aircrafts under different environments before launching the actual physical model. Data collected by DT would aid in future repair by providing the exact geometries of the parts of an aircraft. Safety as well as durability of an aircraft or car can very well be enhanced with the implementation of DTs.

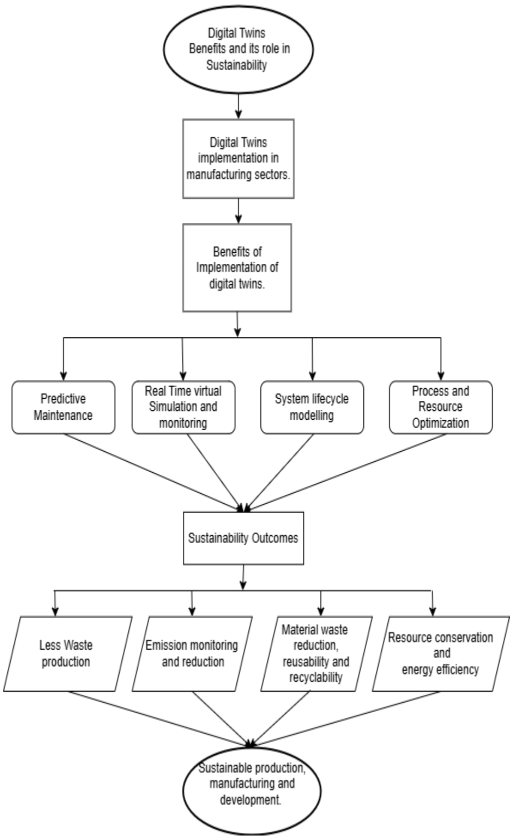
DTs can be used to predict emerging behaviours in a smart city .The real time simulation may be used to monitor urban changes, like new roads or buildings, before implementation.. The composable, API-driven structure of a DT could allow flexible aggregation of complex systems for efficient city management thus making DTs a major component in development of smart cities by helping reduce overcrowding, lower carbon emissions and improve land use efficiency.

Sustainability is one of the biggest global issues faced by this generation. Industries and manufacturing sectors play a major role in contributing to global emissions, energy consumption and waste generation. Thus making this sector more efficient energy wise and consumption wise is crucial and can play a major role in promoting sustainability.

The Industrial Revolution 4.0, connects more systems than ever. For DTs, this means data consistency and information exchange are absolutely critical. The focus is strongly on interoperability. The case studies (port, city, supply chain) show that most DTs are still basic [23]. Some of the DTs reached Level 4 in the maturity model but they are not yet highly automated. Lack of standards: There are not enough agreed rules or formats for how DTs should communicate. Trust issues: People and organizations are hesitant to give DTs too much control. Sharing sensitive data across organizational boundaries raises concerns about privacy, security, and ownership – which affects Level 6 interoperability. Example: Destination Earth. The Destination Earth project is a real-world initiative trying to build a large digital ecosystem with multiple DTs.signs there are active efforts to improve, Standardization, Building trust, Interoperability best practice

As the world becomes increasingly technologically advanced, this generation is seeing an increase in the adoption of technological tools like AI, IoT etc-. Technology offers us powerful tools that give us the ability to monitor, control and analyse things including resources and so technology can play a crucial role in sustainability.

The implementation of a DT in industries and manufacturing companies does not just provide multiple benefits to the company but it can also play a major role in sustainability. Predictive maintenance, real time monitoring and simulation, resource optimization and life cycle modeling are just some of the benefits DTs have which can play a major role in promoting sustainability as explained in section 2.6.2 and in flowchart 4 . The case study discussed in the paper also proves that the practical application of DT in an industry can hold multiple benefits, further strengthening and reinforcing the ground between DT and sustainability[26]. Flowchart 4, shows the explained benefits of DT's when they are implemented in industries and how that can lead to sustainability.



Flowchart 4: The benefits of implementing Digital Twins in industries and manufacturing, illustrating links between different objectives, and its outcomes on achieving sustainable manufacturing, production and development.

For DTs to be effective, companies need to take steps towards sustainability and they should also implement these new and upcoming technologies. The implementation of DTs also possesses challenges as discussed in section 2.6.2. As technology becomes more accessible and developed and as industry standards improve we believe that these challenges will decline. So in the long run implementing a DT in an industry is a great and strategic investment towards efficiency, optimization and sustainability.

DTs are a really powerful technological tool holding multiple benefits. DT's also align with the UN SDGs providing a path for a sustainable future. The current research works on DTs cover mainly technological aspects of it. Further research must be done on DTs in order to improve its effectiveness, scalability and implementation.

Applications of DT can also find its uses in the mining, healthcare, energy, agriculture, oil and gas industries in the coming years as well. With its wide-ranging applications in industry restructuring, increasing production efficiency in manufacturing and assembly and reducing energy consumption, DT technology could become the backbone of industry 4.0 in the coming decades. However the benefits that DT gives make up for these challenges. There are multiple concerns over data theft, cybersecurity, privacy, cost, requirement of vast IT infrastructure and also sustainability concerns over just creating and using DTs. The biggest challenge is that companies and industries are unwilling to implement these new technologies.

DTs have immense potential and will become more widely adopted. They are also redefining how industrial systems are being designed, monitored and optimized. Although challenges such as high initial cost investment and the need for specialized knowledge exist, it is believed that the long-term benefits – both for the company and environment—far outweigh these barriers as government regulations will also push companies to install DTs for emission tracking and resource optimization. As industries continue to evolve toward smarter and more sustainable practices, adopting SysML-based DTs will be a critical step in building intelligent, efficient, and environmentally safe manufacturing systems.

Future advancements in DT's should focus on these areas:

- Implementing 3D models in DTs so that more complex systems in the future can be represented in a simpler model providing greater comprehension and understanding.
- The robust interoperability frameworks and DT lifecycle models are a top priority for future research. As the system of DTs(SoDTs) becomes more common, they need

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standardized ways to connect, share data, and work together.

- The eight "-ilities" modularity, re-usability, interoperability, interchangeability, Verification and Validation (V&V) capability, maintainability, extensibility, and sustainability are the important attributes to make a DT flexible, robust, and cost-effective.
- There is immense potential in using AI and ML to improve these aspects and power sustainable models. Making sustainable DT models called Green Twin models that are sustainable from the creation to usage of the DT because as of today making and using a DT itself uses a lot of resources.
- Cybersecurity and data ethics and its role in DTs. Development of decentralized sharing protocols that hold up security across organizational boundaries.

4. Open research challenges and a Prioritised Agenda for SysML-driven DT's

The literature review indicates that there are structural gaps that are limiting the scalability, interoperability and sustainability of SysML-driven DT's despite their speediness. There are short and long term engineering problems related to these gaps.

Addressing immediate gaps focuses on operational viability. To begin with, the interoperability is embryonic because artefacts defined using SysML are seldomly connected through an IoT or standard simulation engine, so the integration is limited and case specific. Moreover, V&V practices often differ and are inconsistent when it comes to the dynamic evolution of digital twin models with continuous real-time data supply. Thirdly, there is no cohesive mechanism or body for conducting lifecycle assessment, provenance tracking, and data governance.

Systemic limitations are highlighted by long-term gaps. System-to-system interoperability or cross-domain reuse, such as a standardised SysML profile, is hampered by these limitations. It is also crucial to implement lifecycle-aware digital twin management in which these models live through operatings, reconfigurations and end of life evaluation, among others. In addition, nothing currently exists on a resource-aware digital twin that could assess the energy and operational footprint of the models.

5. Conclusion

This review has focused on assessing the usage and potential predictive maintenance of SysML-driven DT's in smart manufacturing and systems modelling by synthesising evidence from across manufacturing, aerospace, automotive, and smart city. From the various studies the most reputable take is that the value provided by SysML is achieved through a unified system model able to link the structure and its behaviours with operational data.

This review highlighted two crucial findings. First, the effectiveness of DT technology for effective mapping is constrained by the limited interoperability between models, simulations, and IoT data. Second, while DT's are claimed to benefit sustainability in the field, a full-scale. lifecycle evaluation remains unfound.

While the review effectively explored the advancements in DTs, such as the implementation of AI and VR, and how DTs can manage to prevent interruptions in the supply chain, there were several limitations faced by the review. First, the review is severely limited due to its reliance on only secondary sources, with the exclusion of any primary data. This prevented the measurement of the effectiveness of DTs' various applications. Second, due to the numerous topics covered - modelling languages, 3D application, sustainability, AI integration - various aspects were discussed briefly, lacking the complete technical depth in specific fields. Additionally, the interoperability or standardization of DTs was not evaluated with a hands on model which only allowed for a general overview instead of exploring the nuances. Despite these limitations, a strong foundation on SysML-driven DT's was set with this review, future research would benefit from industry collaboration, helping validate the authors claims in this review.

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Author contributions

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Competing financial interests

The authors declare no competing financial interests.

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