remote sensing

Review

Digital Twin Technology Challenges and Applications: A Comprehensive Review

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Abstract: A digital twin is a virtual representation of a physical object or process capable of collecting information from the real environment to represent, validate and simulate the physical twin's present and future behavior. It is a key enabler of data-driven decision making, complex systems monitoring, product validation and simulation and object lifecycle management. As an emergent technology, its widespread implementation is increasing in several domains such as industrial, automotive, medicine, smart cities, etc. The objective of this systematic literature review is to present a comprehensive view on the DT technology and its implementation challenges and limits in the most relevant domains and applications in engineering and beyond.

Keywords: digital twin; literature review; enabling technologies; smart city; smart mobility

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1. Introduction

Digital twins (DTs) are an emergent technology which has seen a recent surge in case studies mostly focused on lifecycle management and predictive analysis for various industries and domains. The technology offers the ability to have a deep insight on the inner operations of any system, the interaction between different parts of the system and the future behavior of their physical counterpart in a way that is actionable for their users and stakeholders. DT research and implementation have become more popular in certain domains, such as: smart cities, urban spaces, freight logistics, medicine, engineering and the automotive industry, amongst others. In this work, the DT concept will be analyzed across these domains and across different integration and maturity levels, where the objective is to present both a holistic view of the technology challenges, limitations and trends as well as a domain-specific revision of applications. Not only the technical aspect of DT technology, but benefits, future research agenda and implementation considerations are also explored.

For this work, a systematic literature review (SLR) method is employed in accordance with Charles Sturt University guidelines. Higgins et al. in the "Cochrane Handbook for Systematic Reviews of Intervention" [1] define a systematic review as one that "seeks to collate evidence that fits prespecified eligibility criteria in order to answer a specific research question. It aims to minimize bias by using explicit, systematic methods documented in advance with a protocol". The stages when implementing this methodology are: (i) identifying answerable research questions, (ii) developing a protocol, (iii) conducting systematic publication search operations, (iv) selecting studies to include, (v) conducting a comprehensive revision, (vi) extracting and synthesizing information, (vii) writing and publishing the review. The protocol and selection criteria are evidenced in Figure 1.

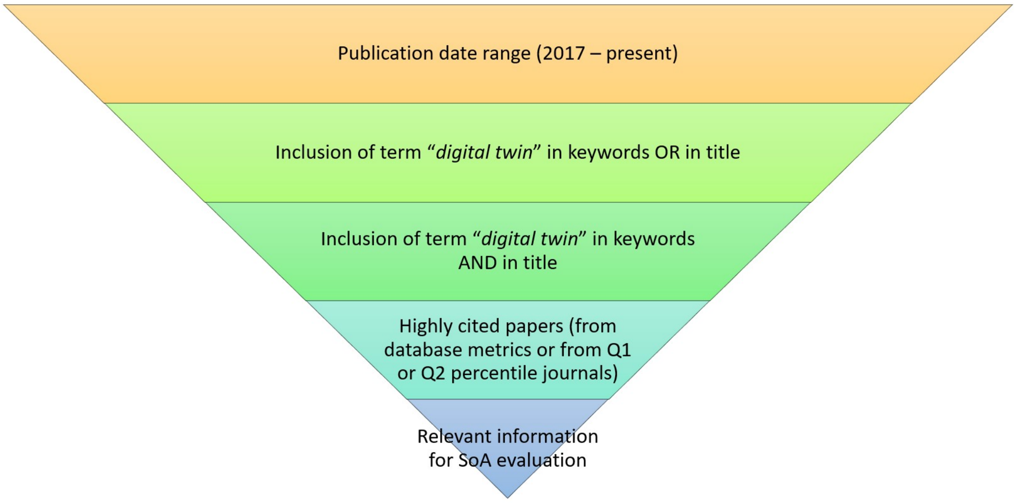

Figure 1. Selection criteria process for publication comparative analysis [2].

1.1. Research Questions

Considering the main objective of this review, a research question (*RQ*) was posed and then deconstructed into three subquestions (*SQx*) to be considered when addressing the main objective.

- RQ: What is the state of the art of DT technology in implementing real-life applications?
- SQ1: What are the challenges of implementing a DT-based system using the current technology?
- SQ2: What are the limitations when implementing a DT-based smart city platform in Latin America and around the world?
- SQ3: What are the trends in the use of enabling technology for the future?

1.2. Contributions

The main contributions that our work is providing to the scientific community are the following:

- **A clear view of trending enabling technologies and specific tools for DT development:** by using the comparative table in Section 4, this work aims to highlight the trends in the use of enabling technologies for domain-specific applications but also for DTs in general. In comparison with other works which only provide a list of enabling technologies, we also discuss the specific tools (sensors, devices and software) in Section 3.
- **Identifying the general implementation challenges around the world and in the Latin American context:** highlighting the centralized efforts from all industries around the world and their different approaches.
- **Building a layered analysis and evaluation of DT applications across various domains** in terms of the integrity level, the technology readiness level (TRL), the societal readiness level (SRL) and the maturity level: using the evaluation tools of TRL, SRL and the maturity index, this paper presents an overview of the state of the art based on real applications and studies.

This work is structured as follows. Section 2 presents the conducted systematic literature review methodology (protocol, systematic search, selection and revision), the DT definitions and concepts, the basic architecture as a holistic view and a maturity spectrum index for DT evaluation. Section 3 describes the application of DTs in various domains and their respective limitations and challenges. Section 4 presents the results and findings on the trends of enabling technologies in DTs and provides a comparison table of enabling technologies for different domains and publications. Section 5 discusses some of the general application challenges, and the challenges specific to Latin America, as well as giving a summary of this work's benefits and implications. Finally, conclusions are provided in Section 6.

2. Methodology

In order to conduct this SLR, the following subsections detail the protocol followed and the systematic approach to literature reviews in accordance with [1]. The compiled studies were selected through specific search methods and criteria and were analyzed to present a state-of-the-art revision on DTs, the general DT architecture, types of DTs, their integration levels and a maturity evaluation method.

2.1. Protocol

A comprehensive search in several databases for publications was conducted. Publications of various types (journal articles, white papers, reviews, etc.) were initially collected. However, the following criteria were set for obtaining a preliminary selection of publications:

1. Search criteria: publications with the term "digital twin" in the keywords or in the title.
2. Year of publication from 2017 to present.
3. Publications were selected from different application industries such as smart cities, freight logistics, medicine, engineering, automotive, etc. The domains discussed in this work were chosen based on their relevance with respect to the initially collected publications.

The classification of publications is based on their application industries pertinent to the third criterion of the protocol and is showcased in Figure 2. As can be observed from Figure 2, the most relevant domains are urban spaces, manufacturing, reviews, engineering, automotive and medicine domains. For this work, the manufacturing domain was divided and automotive-related manufacturing publications were used in the automotive domain section. Additionally, some publications from the urban and engineering domains that relate to freight and operations logistics were also separated. In this sense, the five domains that will be discussed are: smart cities and urban spaces, freight logistics, medicine, engineering and automotive.

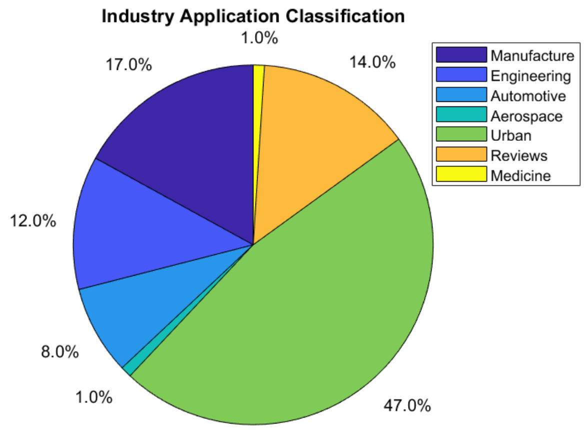

Figure 2. Publication classification by the application industry.

2.2. Systematic Search of Related Literature

Once the searching criteria and publication requirements were established, the next step was to conduct the actual search of the related publications. For this part of the methodology, a variety of databases was used. However, the main databases used were ResearchGate, MDPI, Science Direct and ProQuest. We finally selected articles and publications from recent years (2017–present), and from Q1 and Q2 high-ranked journals (as classified by the Scopus journal search engine).

2.3. Selection

From this preliminary search, a large amount of publications was collected. The total number of publications was 115, and after filtering the highly ranked studies, 84 references were obtained for presentation in this review; moreover, we selected a smaller set of 18 more recent (2019–present) studies that were analyzed in depth and used for a comparative analysis that presents more insights on the trending enabling technologies used in the current applications of DT-based systems. The complete selection process is shown in Figure 1.

2.4. Revision and Synthesis

Once the final set of publications was selected, a comparative table was generated in order to analyze several variables from each publication, such as: the use of enabling technologies, a technology readiness level (TRL) [3], a societal readiness level (SRL) [4], a maturity level [5], the application industry, the system evaluation methods, the construction based on its counterpart physical twin, what sensors were used, etc. This table is presented in Section 4.

One of the challenges that emergent technologies such as DTs face when attempting a widespread and social adoption is the lack of a universal, standardized definition and characteristics. However, there are basic components and ideas of what a DT should do. The authors in [6] mention that a DT must have a physical counterpart to be determined as such. Without the physical counterpart, it is merely a digital model or a digital functional description [6]. Due to the nature of DTs and their applicability to multiple industries and domains, their definition and main characteristics may vary. Recent insights detail all the domains that are currently transitioning and integrating the digital twin modeling concept such as agriculture, electricity, vessels, manufacturing, construction, cities, healthcare, aerospace, waste, water, transport and automotive [7]. This surge in different domain applications comes with more frequent and popular publications on the subject.

2.5. The Digital Twin Architecture

When it comes to specific uses, methods, protocols and even enabling technologies, DT concepts will vary for each domain. This is mostly due to the nature of information from each domain. As declared in [8], each domain will determine the rationale for deploying a DT within a built environment by answering business-case questions. However, there is a general framework for the DT architecture which is composed of three main elements: the physical world, the virtual world and the connectivity between the two [9]. Each element will integrate a variety of components dependent on the designer's needs and requirements. However, some basic components include sensors in the physical world (to gather information from the real environment), a physical twin, edge processing capabilities, data security, the digital twin itself, data processing capabilities (enabled by machine learning (ML), artificial intelligence (AI), big data, etc.) and communication interfaces such as the internet, Bluetooth, satellite, etc. An important part of this DT architecture also includes data visualization for the user. This is showcased in Figure 3, in which the physical world is composed of the physical object or process, sensors, actuators and processing capabilities. The digital world is composed of the digital twin itself, machine learning and data processing capabilities and databases. Both are connected in the communication element where several protocols and interfaces are available such as WiFi, Bluetooth and wired connections. For the user, this architecture allows constant monitoring and visualization.

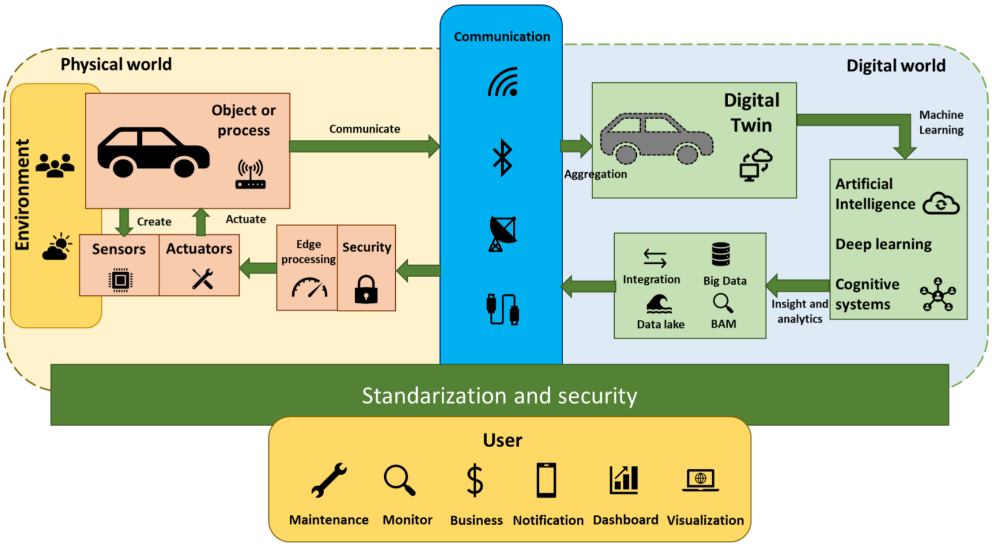

Figure 3. DT architecture [9].

However, the modern state of the art classifies and defines DTs based on the application domain [10] and their levels of integration.

2.6. Types of Digital Twins

- **Digital twin instance (DTI)**: A digital twin instance is described as a type of digital twin that represents its physical counterpart throughout all its lifecycle [10], meaning there is a continuous monitoring of the state of the physical twin and any changes or evolution experienced by the physical twin will impact the digital twin. In this sense, this concept accompanies a product or process from its inception and through its lifetime while monitoring and predicting its behavior. It is useful to validate the expected behavior and performance of a product or object.
- **Digital twin prototype (DTP)**: When it comes to manufacturing and production processes for products, a digital twin prototype gathers and stores valuable information and characteristics about the physical twin. Some data might include computer aided designs (CADs), bill of materials (BOM), drawings or even information that might link the manufacturing process with the production chain stakeholders [10]. In accordance with DT characteristics, the DTP is able to simulate manufacturing scenarios and perform validation testing, evaluation and even quality control testing prior to the actual manufacturing process itself. This approach effectively reduces production costs and operational time by identifying flaws or possible risks of the physical twin before production. In this sense, DTPs can also be called experimentable DTs where, according to [11], a virtual prototype becomes available whose level of detail increases successively while virtual test results give a sufficiently reliable statement about the design quality and reduce the number of usually expensive hardware prototypes.
- **Performance digital twin (PDT)**: In more real and unpredictable conditions for physical twins, the PDT is able to monitor, aggregate and analyze data from products [10]. By aggregating smart capabilities, the PDT is able to process the information being monitored from the physical counterpart and generate actionable data that can be used for design optimization, maintenance strategy generation and drawing conclusions from a product's performance [12].

2.7. Integration Levels

The following integration levels are in ascending order, meaning digital models are the least integrated ones and digital twins are the most integrated, as proposed in [12].

- **Digital model**: In its basic concept, the digital model will not integrate any automatic information flow from the physical world to the virtual world. This means that the virtual and physical world are not automatically connected, so any change must be reflected through manual modification.
- **Digital shadow**: The digital shadow will integrate unidirectional automatic information flow from the physical world to the virtual world [13]. This is best represented by a system where sensors measure information from the physical model and transfer signals to the virtual model. Regardless of whether information flows in a polling or interrupt method, as long as it is automatic, the integration level can be determined as a digital shadow.
- **Digital twin**: A fully integrated twin where the virtual and physical world interact in a bidirectional fashion. This means that information flows automatically to and from each world. In this case, information flowing from the virtual world will be useful to perform changes in the physical model or to instruct actuators to perform an operation. Conversely, data from the physical twin may influence the virtual twin automatically in such a way that the virtual twin accurately represents the current state and the evolution of its physical counterpart.

2.8. Maturity Spectrum

According to a recent report published in [5], the global DT market was valued at USD $3.8 *billion* in 2019 and is expected to reach USD $35.8 *billion* by 2025. The majority of large industrial companies are expected to adopt them in order to increase their effectiveness, but less than 5% of companies have something tangible at the moment. One of the most important insights from [5] is related to a classification of several maturity levels for DTs as presented in Table 1, which are agnostic of the industry domain or the technologies used to build the models. In the literature to date, the majority of DT concepts are at levels 0–3 of maturity, and few have started the integration with real-time data streams due to the significant challenge of data gathering, filtering and processing in real time, as well as device malfunctioning and poor calibration which may create anomalies or missing data points. The 3D simulation modeling with the time component is the preferred approach to date due to the availability of running multiple what-if scenarios powered by real data sets.

Table 1. Maturity levels for digital twins [5].

Level	Principle	Usage
0	Reality capture (e.g., point cloud, drones, photogrammetry or drawings/sketches)	Brownfeld (existing) as-built survey
1	2D map/system or 3D model (e.g., object-based, with no metadata or building information models)	Design/asset optimization and coordination
2	Connect model to persistent (static) data, metadata and building information model (BIM) Stage 2 (e.g., documents, drawings, asset management systems)	4D/5D simulation, design/asset management, BIM Stage 2
3	Enrich with real-time data (IoT, sensors)	Operational efficiency
4	Two-way data integration and interaction	Remote and immersive operations; control the physical from the digital
5	Autonomous operations and maintenance	Complete self-governance with total oversight and transparency

3. Literature Review on Digital Twin Progress by Domain Area

The more general application of DTs can be found in industrial applications [14], inside lifecycle management platforms [15], in predictive maintenance [16] and in the automotive industry [17]. Among the most recent and/or future DT applications, we name: agriculture, healthcare, business, construction, education, mining, natural disaster detection, communication and security [10,18,19]. Another, very complete, review on DT technology remarks on the use of DT in applications for: logistics, robotics, design, manufacturing (production, modeling, experiments and process) and products [9]. The use of DTs for supply networks and service in industrial operations is also mentioned in [20]. Figure 4 shows a summary of the fields of application where DTs and big data can be used, different data mining techniques for prediction, classification and optimization, data acquisition methods (sensors, internet of things) and modeling, as well as the main communication infrastructure technologies [18].

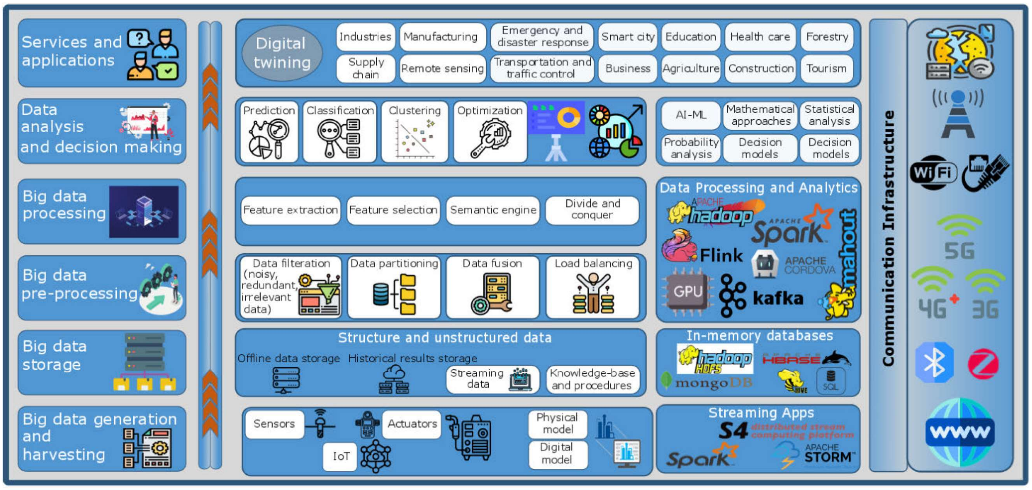

Figure 4. Representative map of features of DT using big data and ML approaches. Several applications and fields are presented, as well as the main technologies and communication infrastructure [18].

3.1. Smart Cities and Urban Spaces

In [21], a smart city is defined as a "strategic approach to integrate data and digital technologies to ensure sustainability, citizen welfare and economic development of the urban environment", where DTs are the building blocks of smart neighborhoods and spaces. Some of the industries that have seen a recent surge in the DT concept integration are smart cities and city planning. Besides the focus around smart digital buildings and their maintenance and asset management, a shift is also taking place towards the digital replica of entire neighborhoods or the so-called smart digital twin cities. City-scale DTs are used to improve the quality of life, mobility and services of the citizens [22] in such a way that technological advances are people-centered and improve the quality of life of citizens rather than achieve economic efficiency [23]. From the studies included in this work, Figure 5 presents the publications of smart digital twin cities being developed in different countries worldwide, where there is a notable increase in density in Europe and China. For instance, this work incorporates three studies [24–26] of smart city DT concepts being developed in China, which presents the highest frequency of all countries. Other publications present advances in cities such as Bogotá [27], Helsinki [28], Brescia [29], Valencia [30], Irkutsk [31], Dublin [32], Herrenberg [23], Shenzhen [26] and Zurich [33] and applications in Europe [34,35]. Recent approaches and initiatives such as Bently's OpenCities Planner in Helsinki, Finland [28] exploit cloud computing capabilities by employing web-based 3D visualization solutions with federated data for communication and collaboration. This is mostly due to the computational burden created by large data sets and cloud points which a web interface with a powerful cloud service behind can easily provide. In [36], the authors present Microsoft Azure digital twins as an approach that integrates different assets and environments ranging from factories and buildings to stadiums and even cities and gain insights from previously disparate devices and business systems. The next step that seems to be taken by Azure DT is in a real-time asset management monitoring even across several factories or cities around the world, with less emphasis on all 3D modeling details and more focus on operational improvement and refinement. Conversely, Dassault Systems [37] are taking the experience to a new level by integrating virtual reality (VR) together with the 3D rendering of the system. Furthermore, authors in [33] discuss that the data must be easily accessible through an advanced geoportal for multiple users in a presentation of 3D spatial GIS models. The authors of [38] mention DT 3D modeling standards in the context of smart cities such as geographic data files (GDFs), CityGML, OpenDRIVE and Open Geospatial Consortium (OGC) standards such as LandInfra.

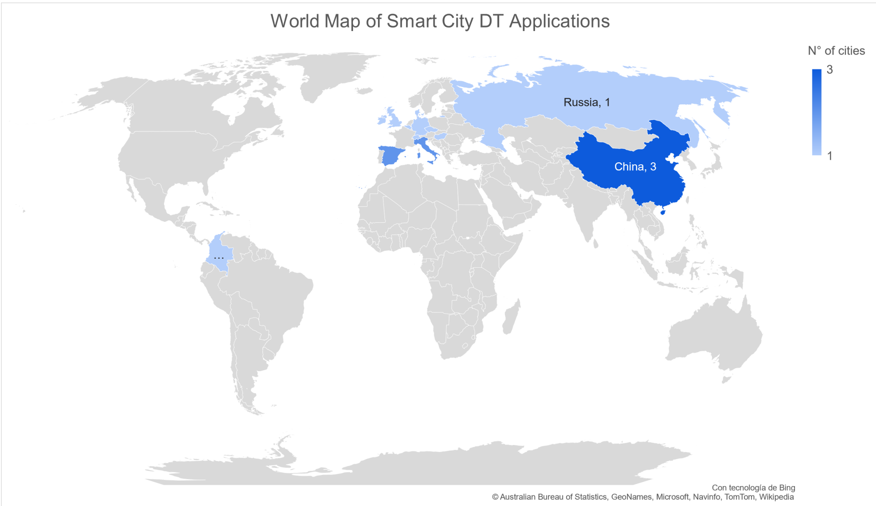

Figure 5. World map of smart city digital twin implementations.

Currently, research scientists are being left behind by several industrial leaders which are moving towards detailed simulation modeling without considering the true and powerful research questions about the capability of such systems powered by big data and AI, which represents a significant gap in some cases that needs to be filled. Several approaches have been taken to start building the DTs of real-life cities by data integration from several sources. This approach generates massive operational data and poses new challenges for diagnosis and prognosis [7]. Big data-based diagnosis and prognosis will be the mainstream research object, including algorithm design, feature extraction, performance improvement, etc. In terms of the SRL for this type of DT, considering the interests of all participants and stakeholders and balancing their utility are the bottlenecks and pose a challenge that still needs to be solved.

In [32], the authors discuss the fact that cities are becoming increasingly smarter and produce information from a variety of sources such as traffic, transportation, power generation, utility provisioning, water supply and waste management. The use of ML and DL techniques has become more relevant as smart cities have become "exciting testbeds for data mining and ML" [32]. The authors defined a DT smart city with six layers as shown in Figure 6. Layers go from the most basic (terrain) up to the digital layer by adding information on different components of an urban space such as building, infrastructure and mobility. Finally, the digital layer has automatic connectivity with the last layer, the digital twin layer where information can be used for scenario simulation and deep urban analysis and studies using ML and DL. In the experimental setup presented in [32], the DT of the urban space uses information from three sources: citizens, IoT data from smart devices and sensors and 3D and urban mobility data enabled by internet connectivity between the DT and the city's council [32]. This work presents an advanced and unique application of the DT technology to perform 3D simulations of a city under different scenarios such as building and infrastructure planning, natural disasters (flooding) and green space simulations. However, in [39] a more advanced and complex work on DT implementations; the Destination Earth initiative is exposed. The European initiative seeks to develop "a distributed and international knowledge platform to facilitate multi-stakeholder collaboration and partnerships, sharing information, best practices, and policy advice among the United Nations Member States, civil society, the private sector, the scientific community and other stakeholders" [39]. In this initiative, information is used to study the set of natural and social phenomena that characterize the Earth system, a class of entities encompassing the local and global changes affecting the natural cycles, the deep under-surface processes and the interconnections with human society [39].

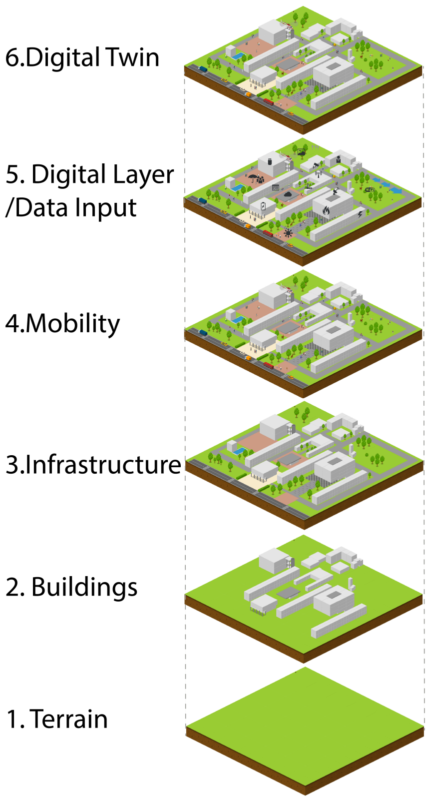

Figure 6. Smart city digital twin layers of integration [2].

Other implementations of DTs as smart city applications can be found in [40] where the authors mention that the latest implementations of smart cities seek to use the information gathered from IoT real-time sensory information to "improve the efficiency, sustainability and security of urban spaces while reducing costs and resource consumption". The study proves the implementation of a multi-paradigm simulation in a DT smart city for citizen surveillance where information is used to generate conclusions on crime prevention, traffic management, energy use and waste reduction in an urban space [40]. The authors discuss that the challenges of a physical implementation of the system would be the analysis of such large streams of real-time data, the reliability and fidelity of the measured data and the challenge of developing simulations for complex dynamic environments. In this sense, the development of multi-paradigm techniques for simulation helps in overcoming said challenges.

On-demand delivery methods such as AmazonPrime, Deliveroo, Uber Eats, etc. are gaining significant momentum, leading to an increase in on-demand personal trips around cities; the complexity of modeling all this behavior currently represents a unique challenge. In [41], authors conclude that "without a sound theory and knowledge with respect to the relationships linking contextual reality and choice/behavior, it is not possible to make sense of what happens in the real world. Therefore, the joint use of behavioral and simulation models should characterize a DT within a Living Lab approach so as to simulate effective, well-informed and participated planning processes, but also to forecast both behavior and reactions to structural changes and policy measures implementations". Furthermore, the implementation of big data in urban space applications enables monitoring of behavioral patterns and lifestyle and their interaction with population, economic development, construction and infrastructure [21]. The authors of [42] rate the application relevance of different types of data in current and future smart cities in percentages with the top five information data sets rated as:

- **Infrastructure data = 91%** (such as data from traffic, renewable energy, industrial appliances).
- **Sensor data = 88%** (gathered by domestic appliances and smart street meters).
- **Smart city IoT data = 86%**(data collected from smart and connected sensor networks in major utility services such as energy, gas and water).
- **Social media data = 86%** (from websites such as LinkedIn, Facebook, Twitter, Pinterest, etc.).
- **Online sources = 85%** (from search engines and websites such as Google and YouTube).

3.1.1. Remote Sensing Technologies

An important part of our analysis is to investigate how sensors are collecting the data, and the main challenges they are facing, such as: cost, sensors not being reliable or calibrated, how to connect the sensors in real time to the cloud or to external servers.

Furthermore, an evaluation of sensing and data analysis solutions for smart cities is presented in [42]. Smart city DTs offer a way of gathering and handling data for automated decision making. Some of the most relevant solutions for urban spaces, mobility and citizen DT concepts are:

- **Real-time demand-based energy production = 86%** (using smart city IoT sensors to determine energy demand and production).
- **Wearables for remote patient diagnostics = 94%** (opening the possibilities of the human DT concept).
- **Body sensors** to monitor chronic conditions = 88% (wearable devices).
- **Real-time information on public transportation and traffic = 96%** (using smart sensing technologies to enhance public transportation and mobility infrastructure).
- **Predictive maintenance for building management systems = 91%** (integrating technologies such as ML and AI to process real information).
- **Drones for site inspections = 88%** (using tools such as cameras, LIDAR and ultrasonic sensors, drones can be used for property management and monitoring).

Other data sources include personal analytics (health data, productivity, fitness, etc.), and large-volume video, images, digital text and audio (from CCTV and public/private records) [42].

Additionally, high levels of fidelity represent some of the major limitations of bringing DTs up to the next level [43]. Modeling all components of a real-life system in detail requires a lot of computational power, storage and data traffic and manipulation on a regular basis. The infrastructure needed to achieve this high level of performance is not attained in many domains such as smart cities. Big data sets would need to be monitored closely in terms of accuracy, frequency and the level of agreement amongst all stakeholders. This gap explains the popularity of BIM as detailed in the following subsection.

3.1.2. Building Information Models

The authors of [44] have proposed a DT evaluation of net-zero energy building (NZEB) for existing buildings; the approach is to combine a novel hierarchy flow chart with a BIM which is then used to thoroughly visualize each option, promote collaboration among stakeholders and accurately estimate associated costs and associated technical issues encountered while producing an NZEB in a predetermined location. Other authors [29] have started to use DTs to conduct a sustainability assessment of an educational building in combination with an IoT-enabled dynamic approach. This is one of the few approaches to date that has shifted towards a maturity level of 3 by real-time data integration with the physical DT model of the building. Some researchers recently brought the DT concept even further [45] by building so-called cognitive digital twins (CDTs) with the purpose of incorporating cognitive abilities to detect complex and unpredictable actions and reason about dynamic process optimization strategies to support decision making in building lifecycle management (BLM). The study relied on surveys with industry experts to focus on the lifecycle applicability and the integration of the CDT model in practice.

The same trend and research questions have been debated by [46] who focused on enterprise BIM (EBIM) as an emerging concept to support business management via the entire lifecycle of buildings and infrastructure. The authors highlight and discuss the importance of both available and missing standards related to the effective implementation of EBIM via a case study focused on cleaning. However, in [29], the authors present a framework for sustainable digital twin (SDT) implementation in an educational building in Italy. This work focuses on the development of the SDT under a green BIM concept that is created in accordance to the International Standardization Organization (ISO) standard ISO 19650-3:2020 [29] which relates to the organization and digitalization of information about buildings and civil engineering works [47]. Although not explicitly related to DTs, this standardization approach is key for the widespread implementation of DTs.

3.2. Freight Logistics

One of the largest sectors in which DTs are making significant progress is the freight and logistics sector, which requires a closer look into decision making taken globally, as shippers and integrators need to act more precisely and choose specific transport modes that obeys strict regulations in order to avoid bottlenecks. For example, the authors of [48] produced one real business scenario where a four-corner model solution enables synchromodality across the logistics network of one industry unit and its providers, the DT for the process and the verified gross mass (VGM) formality documents. They mainly proposed collaboration networks between logistics stakeholders that provide interoperable, low-cost, reliable and secure data exchange, without requiring significant information technology (IT) developments.

In [49], the authors focus on last-mile operations and propose a data- and model-driven framework to support decision making for urban distribution with the test bed being the city of Bogotá, Colombia.In this sense, the DT concept is powered by real sensing data (GPS, RFID and customer service), and using optimization, ML and simulation models, it is meant to simulate different situations and to produce actionable information to support decision making in last-mile operations for retailers. In this way, the methodology is meant to set up potential actionable scenarios to respond to immediate and diverse circumstances [49]. The main data sets used were: a network of stakeholders, the retail organization, the number of vehicles utilized, the resource capacity utilization and the fleet costs. The notion of DT in this work has a special behavior and denomination as it stands for a simulator that can predict future scenarios and can plan strategies for the most likely situations for the dispatchers of various vehicles in businesses (e.g., retail, logistics companies, restaurants). The study uses operational research, deep learning (DL) and data-driven modeling, which is a unique combination without any 3D modeling or realistic city layouts involved in the work.

The authors of [50] mention that "to advance the competitiveness of services, retailers and logistics service providers have devoted significant effort to deploy express fulfilment services, e.g., same-day or next-day delivery, via an omni distribution channel. This results in new logistics challenges such as fragmented and downsized shipments, higher delivery frequency, shorter delivery time, highly fluctuation and uncertain demands and returns". This comes as a result of the modern e-commerce behavior which demands an increasing fragmentation, complexity and integration level of DTs. Recent works with regards to ports [25] mention that the DTs for ports should focus on port digitization and integrated management needs, based on the BIM plaform, an index system of anchorage, quay crane, port machinery and gate infrastructure and effectively integrate the sensing information of the data. For this, tools such as Anylogic, Simio, Arena and Transmodeler can be used for scene visualization and management coordination, full scene of the port development process and the integration of the port planning, design, construction and future operations.

Another challenge is related to the complexity of urban planning in megacities [50] which significantly delays all freight and logistics operations—see the example of Seattle where freight vehicles spend 28% of their trip time finding available parking.

3.3. Medicine

Implementations of DTs in medicine have recently started to be reported in the literature [51]. Diverse applications have been described, such as in the fields of fitness [52], simulations of viral infection [53], well-being in smart cities [54], remote surgery applications [55] and healthcare management [51].

Healthcare management can benefit greatly from DT technology; the use of AI, data science and DL approaches can be used to provide more customized (and faster) healthcare services to the population. Usage of such technologies has served to develop technologies such as vital sign monitoring apps, brain–computer interfaces (BCIs), food monitoring apps and liver and cardiac disease detection. The conceptual model of a human digital twin (HDT) is proposed in [51], framing security and social ethics problems among its main challenges. Its objective is to replicate the body of a person in a cyber-physical space using information provided by wearable sensors, mobile phones and medical records continuously updating its content via web services [51]. The data are analyzed by different tools to provide contextual interpretations of the health state of the patient. Some other elements are taken into consideration such as the interaction between other people and the environmental factors. The idea of the HDT involves a particular index that is provided to humans when they are born, and their biological information is constantly fed as an input to the HDT as the person grows.

One of the biggest challenges of the HDT is that although some variables can be monitored to infer certain threats, other human traits, such as thinking, reactions and behavior, can be, to some extent, unpredictable, because humans are more complex than manufacturing processes. Another one is that humans, if seen as models, are not independent from one another. Factors such as genetics, heredity and even culture might play a role in determining differences in specific human features [51].

In [52], a set of HDTs was developed for a team of athletes. Variables such as heartbeat, number of steps, physical activity and sleep time, as well as manual information about the food intake, their performance and mood, were recorded. The SmartFit app is explained in this study, where the information is gathered, and sent to predictive models; the outputs of the models are presented to trainers and coaches in a user-friendly visualization, which can be used for correction, monitoring and suggestions. ML and DL algorithms can be used to fill in the blanks or to manually correct fed data, by choosing reliable predictors that take into consideration both past and future values. A challenge from this type of DT is that the amount of data and the processing time needed to build individual models constantly increase. Incremental learning is suggested to learn "on the run", as new data become available.

In a recent work [53], the description of a DT used to simulate human response to viral infections is presented. This DT is built at different scales: subcellular, multi-cellular, tissue, organ and whole-body scales, each simulating specific parameters related to a viral infection at those scales. The experimental part of this DT is imperative as data coming from sensors and medical records will be key to the development of reliable predictions through the simulations. In [56], the authors also propose an approach of a collaborative city DT concept capable of generating information for city crisis management. In another work, a city-scale platform for interacting DTs was used to enable data-driven decision making and to generate efficient and inclusive plans to manage health crises, such as the COVID-19 pandemic [56].

Among the main challenges for this type of DT is the fact that many biological phenomena are poorly understood, such as infections within the body and the immune response to viral pathogens, as well as some treatments. Therefore, validation by experts is very important in order to assess the reliability of the models [53].

A DT for well-being is presented in [54], where an ISO/IEEE 11073 (X73) standardized DT was developed. This development follow protocols and guidelines internationally validated for data collection in personal health devices. A custom-made system was developed to measure in real time gait forces using sensors in shoe insoles to identify if the participants were walking, running or sitting. Visualizations were also enabled and the authors suggested that the use of such systems in the smart city context could improve the quality of healthcare services that are available to citizens [54]. In [57], the authors proposed the use of HDTs for elderly real-time monitoring, remote diagnosis, virtual surgery training and health consultation. By analyzing all the physiological variables of the patients constantly and in real time, the system could send alerts to cloud servers, where medical workers and/or institutions have access to the information, and then perform preventive or emergency measures [57]. Figure 7 shows a representative framework for HDTs according to [57].

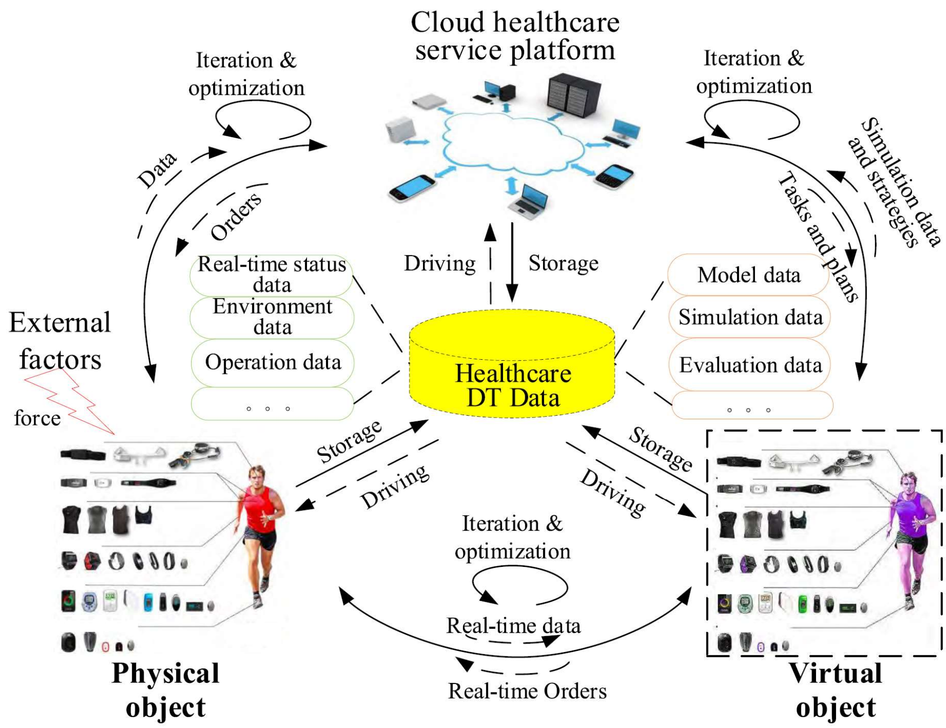

Figure 7. Framework for DT used in healthcare: data are acquired in real time from wearable sensors, and sent to models for simulation and evaluation. The historical records are recorded in the cloud to provide personalized healthcare services [57].

3.4. Engineering

The DT concept is key for modeling, simulating and optimizing cyber-physical systems [58]. It can provide a deeper understanding of complex physical processes through application services concerning diagnosis, simulation, monitoring, optimization and prognostic and health management [7]. Thus, DTs enable companies to make more accurate predictions, rational decisions and informed plans [59].

The engineering applications of DTs seek to predict the future behavior and the performance of a physical system (predictive) and build a relevant industrial big data that allow the self-adaptive behavior of the equipment, providing support in the decision-making process (interrogative) [24,60]. Although a DT does not necessarily imply a spatial/visual model, the application of AR and VR for simulation, via the DT, is a safer approach (with extra features) that allows working with hazardous environments and remote access [61]. According to the literature, around 18% of engineering applications of DTs focus on design, approximately 35% on production areas, 38% on prognostics and health management (PHM) and 9% on other areas [59]. However, the application can be diverse depending on the stage of the engineering product lifecycle such as design, manufacturing, distribution, usage and even end of life [62].

In [11], the authors proposed a DT-based simulation framework to equip virtual testbeds with efficient algorithms, in combination with up-to-date virtual reality and 3D simulation techniques. This sought to reduce the development costs and the time to orbit for the iSAT-1 space mission. A different study developed an advanced physics-based model to enable predictive maintenance applications focusing on the dynamic behavior of the machine, the virtual sensors and the modeling parameters [63]. Meanwhile, another study integrated a six degrees of freedom (DoF) robot with an end-effector grinder and a computer vision system, to create an automation cell for a fan-blade reconditioning component of maintenance, repair and overhaul (MRO) services. Here, a DT of the grinding process was developed to explore the required force parameters to remove surface material [64]. In general, applications in this area focus on predicting aspects such as the structural life of the aircraft, the operational state of sections, the tire touchdown wear and its probability of failure, the cooling rate and the temperature gradient, among others [59].

An example in construction is a DT multi-dimensional model that was developed to achieve real-time monitoring of prestressed steel structures and provide timely predictions regarding safety [65]. Moreover, a vessel DT-denominated "virtual sister ship" was proposed by DNV GL to both reduce operational cost and increase reliability and safety while a different application focused on a drilling platform DT for Blue Whale 1 (China) to enable a visual display and real-time monitoring [7]. One more case is the successful application of DTs in electrical energy conversion systems, particularly cabling or cable systems, which allows for calculating the aging time through the cable current condition [24]. Other diverse applications can be found in vertical transportation systems, where DTs can be used to evaluate the system condition and potential corrective solutions derived from friction losses, vibration and discomfort [66]. The authors of [67] present a DT model in the context of high-voltage transmission line live working scenes for simulating a live worker posture trajectory, including geometric, electrostatic field and safety operation components. This DT sought to realize the deep fusion of physical trajectory and spatial virtual electric field distribution of a live worker operating across different scenarios.

Nonetheless, a robust simulation requires precision, accuracy, data acquisition and synchronization [24]. Hence, the practical implementation of DTs faces obstacles such as real-time communication, complexity, accuracy, integration and structural foundations. The challenge of running the DT in real time is not only related to the need for re-running the optimization algorithm, but to the migration of the DT from one edge server to another [68]. Alongside the high variability and uncertainty, the complexity of the real industry context can generate more equipment interactions that involve conflicts between resources, limiting the high-fidelity mirroring of the physical system [60]. Some argue that a DT should be simple enough, so it provides a reasonable estimation of the product/operation, risking the accuracy [63]. On the other hand, the functionality and behavior of a system depends on the correct interaction of modules with a local intelligence [11]. Due to the different formats, standards and protocols, current tools are not integrated and simultaneously used for a specific objective [7], and production plants do need tools that can centralize (at least partially) the flow of decisions [60]. In the future, the development of platforms and tools for DTs is required [7], as well as more efficient mapping systems, novel control interfaces, flexible data visualization and overall simulations [15]. Specific to integration, some opportunities include VR, cloud/edge parallel computing and the incorporation of big data analytics [15]. Finally, the security and privacy of the DT should be carefully studied [59].

3.5. Automotive

In the automotive industry, although there has been an increase in the use of DT concepts, most of the existing work is focused on the automotive manufacturing processes and prototype testing. A key enabler of data-driven manufacturing is the concept of the DT [17]. The authors of [6] mention that the key benefits from DTs are "increased productivity, reduced complexity, time savings, reduced cost, improved quality". The authors also mention that DTs can be used to develop and optimize new and existing products [6] by generating information that is not readily available in the real environment [69]. In this sense, once the physical counterpart exists, there are different configurations of DTs in the automotive industry, such as the following (each configuration will have an impact on different stages of a vehicle's lifecycle from its conceptual design, to the system engineering design, manufacturing, testing, performance and its end of life).

- **Functional prototype twin (FPT twin)**: This is the basis for a functional representation of the vehicle using model-based systems engineering.
- **Harness twin**: A DT that aims to represent and optimize complete wiring harnesses in the vehicle.
- **Prototype twin**: Representation of a fully developed vehicle that is useful for scenario simulation. This may have a great impact on reducing time and costs in testing phases and future design and development stages.
- **Geometric twin**: Geometric prototype of the vehicle that integrates information on the physical manufacturing and assembly of the car as well as information necessary to connect individual car parts.
- **Virtual reality twin (VR twin)**: Visualization twin that presents a visual aid for simulation, rendering and optimization of manual assembly work on the vehicle.
- **Simulation twin**: Primarily used to develop software solutions or updates for existing car models. Has the capabilities of experimentable DTs.
- **Reuse twin**: Digital representation of the end of the lifecycle of the vehicle where information is enabled to draw conclusions on recycling strategies and optimization solutions for a new series of vehicles.

In [70], an advanced approach is presented for an X-in-the-loop (XiL) framework and demonstration for exploiting new technologies such as DT and IoT to provide connectivity between physical and virtual representations of a vehicle during testing. The XiL framework is put to practice in test and validation environments for a vehicle with various integrated systems such as real-time vehicle simulation (vehicle-in-the-Loop), test and validation functions from the automotive segment, artificial urban testing environments for automated cars, connectivity platforms and interface applications [70]. With a mixed reality approach, the study aims to prove key benefits from such integrated ecosystems such as reproducibility, flexibility, scalability, cost efficiency and realistic simulation [70]. Some enabling technologies present in the demonstration are industry-standard simulation tools such as CarMaker VTD, CarSim and PreScan and sensors such as light detection and ranging (LIDAR), radio detection and ranging (RADAR), Global Positioning System (GPS), inertial measurement unit (IMU), controller area network (CAN) bus and cameras [70]. The simulation framework for an implemented proof-of-concept scenario-in-the-Loop (SciL) validation model from [70] is presented in Figure 8.

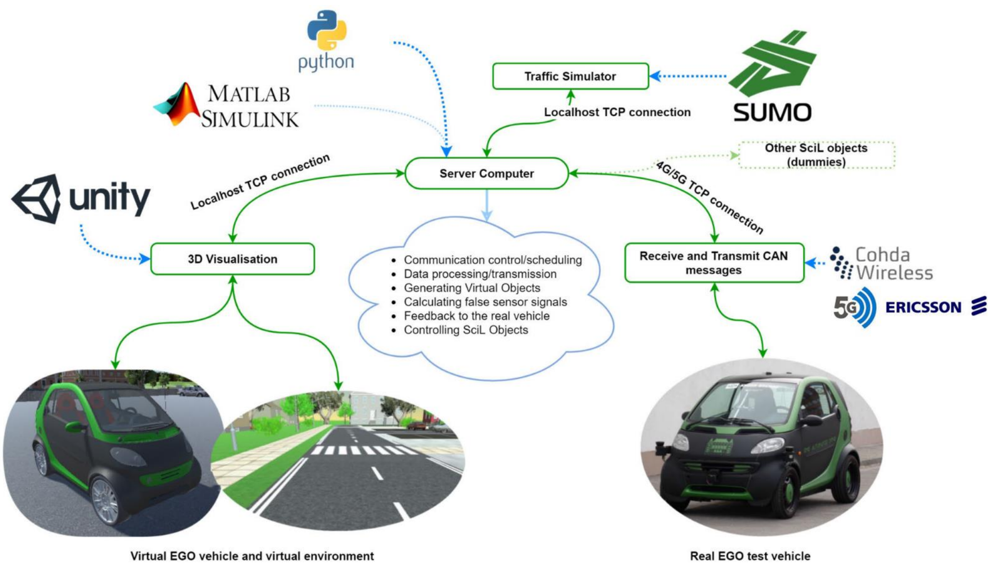

Figure 8. Co-simulation framework of the implemented proof-of-concept SciL validation model. Real-time interface between several simulation tools incorporates different wireless communications and adds realistic visualization and co-simulation techniques which create unprecedented opportunities for software tool combination [70].

Electric Vehicles

In [71], the authors discuss the importance of enabling technologies in the advancement of electric vehicles in the automotive industry, with the introduction of IoT and network technologies that convert offline digital models to DT; this presents important benefits such as smart system monitoring, prediction and re-scheduling of upcoming maintenance events, fault locations, fault endurance and remaining useful lifetime [71]. DTs have been identified as enablers for further optimization of the efficiency and reliability of electric vehicles (EVs). In addition, five enabling technology trends are outlined: IoT, cloud computing, application programming interfaces (APIs) and open standards, AI and digital reality technologies [71]. In this case, the authors propose three classifications of DTs in the automotive industry: digital twin for design (DT4D), digital twin for control design (DT4CD) and digital twin for reliability (DT4R) [71].

In an application of an electric battery DT for an EV, some authors provide a framework for integrating concepts of state-of-the-art battery modeling, in-vehicle diagnostic tools and data-driven modeling approaches [72]. The authors also propose a potential ecosystem of battery DT data aggregation where multiple vehicles produce real-time information that is sent to the cloud via IoT and is accessible for external users. Some technologies that are present in this work are AI and ML models that enable data mining and data refining, ML for remaining useful life (RUL) estimation of components, cloud and edge computing, IoT and data-driven modeling. The use of these technologies together with the aggregation of multiple data sets, real-time monitoring of key states and the fusion with hybrid models unlocks the potential for optimizing real dynamic systems such as battery systems [72]. The cyber-physical elements of the battery DT proposed by [72] include: data collection, data processing, model/algorithm application (through edge and cloud computing), cell balancing, battery diagnostics, SOX estimation, smart charging, energy management, system prewarning and remote upgrade and maintenance and a mirrored framework of functions and operations [72].

In the category of EVs, these present a challenge to design engineering due to the fact that most of the components involved are multi-physics systems incorporating interactions of mechanical, electronic, thermal and other phenomena [73]. This makes multi-physics modeling an important part of DT implementation for EVs. According to the authors, “the design and operation of e-powertrain components requires the consideration of their multi-physics effects and the coupling between them, as well as the interactions of the components with the rest of the EV and its environment" [73]. Vehicles can be classified as systems-of-systems which adds to the complexity of representing cars in a virtual world. However, [73] propose the use of model order reduction techniques to enable the real-time model-based health assessment of e-powertrain devices in representations of reduced complexity.

4. Results and Findings on Enabling Technologies

In accordance with the SLR methodology, the final steps of our current work focused on gathering and comparing a small set of studies (18 for this work). These studies were compiled using every criterion in our methodology and are summarized in Table 2, where enabling technology trends, TRL, SRL and maturity levels are presented for each domain. In order to target our research subquestion *SQ3*, we conduct the final comparison of studies which provides valuable information towards understanding the most relevant enabling technologies in terms of computing, simulation, communication interfaces, data analysis techniques, sensing technology and evaluation methods for future DT development. For evaluating different publications, a TRL, an SRL and a maturity spectrum index (only for implemented applications) were assigned. As presented in Table 2, most applications lie in the early stages of DT development and levels of these evaluation methods, indicating the infancy stage of DT implementations and the large gap to fill.

The TRL is an index proposed by the European Commission where a scale of 1–9 rates studies in terms of technology readiness level (e.g., implementation and validation level) [3]. The levels are presented as: (1) basic principle is observed, (2) technology concept formulated, (3) experimental proof of concept, (4) technology validated in a lab, (5) technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies), (6) technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies), (7) system prototype demonstration in operational environment, (8) system complete and qualified, (9) actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies, or in space).

The SRL assesses the level of societal adaptation of the studies with nine levels where levels 1–3 reflect the early work in a research project, including testing on a preliminary basis of a technical and/or social solution to a societal problem. Levels 4–6 represent the actual solution, the research hypothesis and testing it in the relevant context in co-operation with relevant stakeholders, while keeping a focus on impact and society's readiness for the product. Levels 7–9 include the end stages of the project, refining the solutions, implementation and dissemination of results and/or solutions [4].

The findings in Table 2 show that some technologies such as ML, big data, remote sensing, IoT and cloud computing are common across all domains and are therefore the most relevant when it comes to DT implementation in general. Each domain demands specific tools for development, but the most common are GIS modeling, ANSYS, ML data processing, big data, GPS/LIDAR sensors and IoT communication using various interfaces. All domains present advanced and mature implementations with most of them classified at level 3 of the maturity spectrum (where models are enriched with real-time and static data). The TRL evaluation also presents high levels of technology readiness, especially in the smart cities and the automotive domains. This may be an indication of the slower adoption of DTs by the smart manufacturing, freight logistics and medicine domains, due to implementation costs and complexity limitations. In addition, all domains show low levels of societal readiness. This is representative of applications where relevant stakeholders are not identified or consulted, and the potential impact on society and the environment is not well defined. Moreover, the smart cities and medicine domains should lead the way with sustainable development frameworks given their high societal impact.

Table 2. DT application technological comparison.

Domain	Ref.	Objective	Physical Twin	Computing	Simulation	Communication	Data Analysis	Sensors	Eval.	TRL	SRL	Matur. Level
Smart Cities and Urban Spaces	[30]	DT for water distribution system	Water distribution system	-	GIS	IoT	Big data	Level, pressure, flow, quality, etc.		7	0	3
Smart Cities and Urban Spaces	[74]	Smart city management	Urban Space	-	ArcGIS	-	ML (ICP, C2C, M3C2), Big data	LIDAR, UAVs, satellites, ranging sensors	-	3	2	2
Smart Cities and Urban Spaces	[21]	SoA of implemented DTs	Urban Space	Fog/cloud computing	ANSYS	Bluetooth, NFC, MQTT, HTTP, Ethernet	ML (ANN, CNN)	Camera, pressure, vehicle GPS, travel cards, temp., etc.	-	3	1	-
Smart Cities and Urban Spaces	[31]	Electricity network DT	Electricity distribution network	-	Python	-	Reinforcement learning (Markov decision process)	IoT electricity meters	77-node test scheme	4	3	3
Smart Cities and Urban Spaces	[29]	Implementation of SDT	Educational building	-	OPAL-RT	IoT, Ethernet, LoRa	AI	Temp., humidity, light, CO_2, VOC, sound, etc.	Sustainable building rating systems	7	4	3
Smart Manufacturing	[75]	Lifecycle monitoring and business projections	Industrial machines	Cloud	-	JSON, IoT, REST API	ML, Big Data	-	-	8	0	3
Smart Manufacturing	[60]	Implementation of smart manuf. cyber-physical system prototype	Manufact. process, AGV	Arduino (edge)	DES	WiFi	Indus. Big Data	Proximity	-	5	0	1
Smart Manufacturing	[76]	Role of DT in manufacturing	-	-	Matlab/Simulink, Mathematica, Dassault Systems	IoT	Big Data	-	-	-	-	-
Smart Manufacturing	[77]	Framework for CPPS-DT implementation	-	Cloud	V-Hub	IoT (MQTT, OPC, WebSocket)	Indus. Big Data	-	Continuous model calibration	7	2	3
Freight Logistics	[49]	Proposing data- and model-driven framework for urban logistics DT	Distribution network	-	GIS	Mobile	ML, DL, AI	GPS, RFID, customer service	Walk-forward metric	7	4	3
Medicine	[54]	Framework for HDT	Human	Cloud	-	X73	ML (CNN)	Wearables	-	3	3	2

Table 2. *Cont.*

Domain	Ref.	Objective	Physical Twin	Computing	Simulation	Communication	Data Analysis	Sensors	Eval.	TRL	SRL	Matur. Level
Engineering	[40]	DT for surveillance	Urban space	-	Multi-paradigm	IoT	Markov decision process policy generator	Camera, drones, seismic, humidity, audio, etc.	-	3	2	-
Engineering	[65]	Multi-dimensional DT for prestressed steel	Steel cable	-	ABAQUS, ANSYS	Serial	ML (SVM)	Pressure transducer	Error percentage	5	0	-
Engineering	[63]	Methodology for advanced physics-based PdM modeling	Industrial robot	-	Open Modelica, Matlab	-	-	Virtual sensors	-	5	0	3
Engineering	[64]	Automation for reconditioning of aircraft component using DT	Industrial grinding robot	-	Coppelia- Sim	-	Markovian chain	RGB-D camera, depth and force sensors	RMSE	6	0	3
Automotive	[69]	Battery pack DT for monitoring	Battery pack	Cloud	-	4G IoT (MQTT), REST API, HTTP	Python	GPS, OBD-II, voltage, acc., etc.	-	7	0	2
Automotive	[70]	DT for vehicle testing	Car	Cloud	Unreal, Matlab/ Simulink, Python, CarSim	5G	ML, AI	LIDAR, RADAR, GPS, CAN	Accuracy testing, ISO standards	7	3	3
Automotive	[78]	DT for automotive LIDAR	LIDAR	-	ANSYS	-	ML (NN)	LIDAR	Accuracy and precision testing	4	0	-

5. Discussion

5.1. Application Challenges and Limitations

The authors of [10] argue that the challenges that might arise depend on the scale and integration complexity of the application. From the reviewed literature, five main challenges that are common for all domains were found in DT technology implementation. These challenges effectively conclude and respond to the research subquestion *SQ1* and help address the state-of-the-art main research question (*RQ*) :

1. **Issues related to data (trust, privacy, cybersecurity, convergence and governance, acquisition and large-scale analysis) [10]**. It is difficult for designers to mimic or model behaviors that cannot be explained by numbers. Such is the case of social conflicts, sociopolitical issues, social inequality [79] and environmental sustainability [80]. These developments in the social and environmental domains will target lower levels of SRL where there is a clear understanding of the potential impact on identified stakeholders, the entire society and the environment. Furthermore, this challenge relates to maturity levels 3 and 4 in Table 1 where enriching models with real-time and bidirectional flow of information presents a relevant limit when it comes to complex DT implementations.
2. **Lack of standards, frameworks and regulations for DT implementations [15]**. The authors of [77] discuss that implementations of DTs are limited due to a lack of standards and recognized interoperability, especially in the manufacturing domain. Articles that explore the benefits, define concepts and architectures of DTs and review the technology's state of the art are important for adopting a widespread, concrete understanding of DTs and their relevance. Furthermore, targeting this specific challenge with surveys and literature reviews, researchers may impact lower levels of the TRL to make basic principles and concepts widely known.
3. **High costs of implementation due to the increased amount of sensors and computational resources needed [10,18]**. Due to the expensiveness of DT implementations, their accessibility is limited by the accessibility of such resources, which is often poor in developing countries [79]. The increase in the amount of sensors needed comes with an added complexity with regard to data connectivity and processing which poses a challenge to reach level 3 in the maturity spectrum from Table 1 (where the digital model needs to be enriched with real-time information). This challenge also poses a limitation for practitioners to enable higher levels of TRL where pilot systems are demonstrated, DTs are incorporated in a commercial design or full-scale deployment.
4. **The use of AI and big data to satisfy the long-term and large-scale requirements for data analysis [13,81]**. With the large amount of data generated and analyzed in DT systems, big data algorithms and the IoT technology are powerful allies that can provide support to a great extent to successful DT implementations [75]. Furthermore, information flowing from various levels of indicator systems presents a challenge for developing common policies and standards [82]. Effectively targeting levels 4 and 5 of the maturity spectrum, this challenge could enable bidirectional flow of information, control of the physical world from the digital model and even autonomous operations and asset maintenance.
5. **Communication network-related obstacles**. There is a need to build faster and more efficient communication interfaces such as 5G. The authors of [42] mention an urgent demand for using the 5G technology for smart cities, such as the ability to connect many more sensors and devices, the high-speed ubiquitous connectivity, the improved reliability and redundancy and ultra-low power consumption; the authors believe that it is of great value to enable real-time data connectivity and operational efficiency for the DT.

5.2. Digital Twin Challenges in Latin America

It is important to note that the development and widespread implementation of DTs depend on the advances in research and enabling technologies such as AI, ML, big data, 5G communication and cloud/edge computing [10,83]. Addressing research subquestion *SQ2*, in the Latin American context, the challenges are greater due to limited access to high-end technology in developing countries as exposed by [79]. This, paired with a lack of interoperable platforms and tools with up-to-date information under set standards, presents a significant obstacle to DT implementation. However, applications in Latin America offer significant opportunities for environmental and sustainable development [27]. To make cities more sustainable, the design and practice of buildings as well as the perception and lifestyle of citizens would benefit from smart city DT implementations. With the gained insight from an urban space, developers and designers may use the information for proposing solutions to reduce urban expansion, reduce carbon emissions, integrate the use of renewable energy sources and optimize infrastructure and construction methods. Furthermore, the DTs may generate actionable intelligence necessary for addressing global challenges, facilitating sustainable transitions and contributing to realizing the United Nations Sustainable Development Goal (SDG) agenda [39].

5.3. Contribution Benefits and Implications

Our work presented in this paper explores the possibilities, challenges and limitations for DT implementation and its use in different domains. By understanding how DT applications might differ in terms of their requirements, data gathering techniques, data processing, simulation and prediction capabilities, a more concrete and general understanding of the benefits and implications of this technology is made available. Other literature reviews such as [9,13,62,84] focus on presenting the DT architecture, definitions, concepts and benefits while others, such as [15–18], focus on the technical aspect of the DT technology and explore the trending technologies for a solid DT implementation. Our work explores both perspectives and adds a discussion of a future agenda for researchers and practitioners based on real applications and the state of the art of the literature. In this sense, the main research question (*RQ*) is addressed and subquestions (*SQ1, SQ2, SQ3*) are answered in a comprehensive approach. The findings presented in this work help to answer our research questions but also open the discussion for future research developments in this field.

To reach a widespread implementation, industries and organizations need to clearly understand the benefits of implementing DTs in their processes. In this sense, this work presents a clear overview of how each domain is impacted by this emergent technology. Furthermore, a holistic view of benefits, challenges and future agenda is presented to discuss DTs in a generic way which is crucial to making these insights transferable across domains as suggested in [17]. The challenges presented in this section present a clear view of the current limitations for more mature and complex implementations of DTs across all domains. Furthermore, the layered analysis and evaluation using the TRL, SRL and the maturity spectrum present valuable information on the state of the art of DTs. For instance, the presented challenges show the relationship of specific enabling technologies and their relevance to creating more mature DT concepts (beyond level 3 of the maturity spectrum in Table 1). Additionally, Table 2 presents a pattern that shows that most DT applications have not been developed to high levels of SRL. This suggests a point of improvement when it comes to developing more sustainable and society-centered applications where communities, governments and stakeholders are taken into account. The discussed challenges present a guide for practitioners and researchers to focus on specific aspects faced in real applications when developing the DT technology.

6. Conclusions

The emergent use of DT applications across a number of domains is on the rise and, combined with enabling technologies such as big data, ML, advanced modeling, simulation and advanced communication interfaces, it enables insights on their physical twin's operation in a way that is useful and actionable by the designer or the operator. This insight leads to a data-driven decision making, which in some domains is the main advantage of DTs. In the different domains presented in this work, their respective concepts of DTs have different focuses and needs. For instance, some key features, such as real-time monitoring, predictive analysis or edge/cloud computing, will differ in terms of relevance but the main concept and basic architecture of the DT are still prevalent across all domains. Although universal standards for this technology still lack widespread adoption, the increasing amount of publications and attention towards DTs is an important step for standardization organizations such as ISO to take DTs into account. It is well noted that the predictions for the DT market are favorable, where market value is expected to increase significantly as more companies and industries adopt the technology. Not only in the private sector, but also governments and public agencies are starting to consider and implement DT concepts for smart city developments, public services management and an overall insight into their urban communities. The use of urban spaces and human health DTs is aligned with citizen well-being and Sustainable Development Goals which target a framework of sustainability for DT development.

DT technology is still in its early stages and reaching its full potential will require addressing significant limitations and challenges for a modern DT implementation, such as: costs, information complexity and maintenance, a lack of standards and regulations and issues related to cybersecurity and communications. The TRL, SRL and maturity spectrum evaluation of relevant publications is of great value to assess DTs in three aspects: technology, societal readiness and maturity. As seen from the analysis in Sections 3 and 4, the technology and maturity of DTs are still in early stages for most applications. Table 2 includes advanced applications of DTs, but more work needs to be done to fully enable autonomous, sustainable and accepted DTs in real environments. As technology further develops under the framework of innovation and sustainability, these and other obstacles will become easier to tackle. Technologies and tools for data processing and analysis will be key enablers for further improvements in DTs. Based on the challenges presented in this work, future research efforts should include: (1) simulation and modeling techniques to reduce computational complexity; (2) 5G communication; (3) IoT data processing and analysis through big data, ML and AI; (4) interoperability and integration of simulation, modeling, analysis and visualization software; and (5) edge and cloud computing capabilities in advanced microprocessors. Understanding the holistic view of DTs across many relevant domains will allow for a better evaluation of the state of the art and where the technology is going. It is essential to address the proposed research efforts to unleash the potential of DTs for the future.

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