Framework for knowledge transfer

D2.4 Selection of Existing data-intensive Models and Tools

Selection of specific existing data-intensive models and tools for digital twin technologies that can be transferred

EU-CONEXUS ENABLES

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Acronyms

Acronym	Full Form
FredU	Frederick University
UTCB	Technical University of Civil Engineering Bucharest
UROS	University of Rostock
UNIZD	University of Zadar
SETU	South East Technological University
LRUniv	La Rochelle Université
UCV	Catholic University of Valencia
KU	Klaipeda University
AUA	Agricultural University of Athens
ONU	Odessa National University

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1. Executive summary

This document outlines the selection of existing data-intensive models and tools relevant to digital twin technologies, particularly in the context of the EU-CONEXUS ENABLES project. It emphasizes the importance of digital twins in various sectors, including the built environment, agriculture, and life sciences.

Digital twins are virtual replicas that simulate real-world systems, allowing for real-time monitoring, predictive maintenance, and enhanced decision-making. The report discusses how these technologies can optimize operations, improve sustainability, and facilitate knowledge transfer among partners involved in the project. Key areas of focus include the integration of data from sensors and IoT devices, which enables better management of resources and infrastructure.

The document emphasizes the importance of knowledge transfer from non-widening partners, highlighting their initiatives in developing digital twin models that integrate real-time data, simulations, and predictive analytics. Some chapters involve reviewing existing digital twin models and tools to identify those that align with the project goals and have the potential to be transferred and replicated.

Overall, the framework serves as a guide for leveraging digital twin technologies to address specific challenges and enhance knowledge sharing across various domains.

2. Introduction

This document is organized into several key sections that systematically address the selection and application of data-intensive models and tools relevant to digital twin technologies within the context of the EU-CONEXUS ENABLES project.

Specific applications of digital twins are presented in the sections, starting with the **Built Environment**, which explores how digital twins can enhance infrastructure management and urban planning. This is followed by a detailed examination of **Agriculture** and **Life Sciences and Medical Applications**, highlighting the transformative potential of digital twins in optimizing agricultural practices and improving healthcare outcomes.

The document also includes a **Comparison of Tools** utilized across these sectors, providing insights into the commonalities and differences in their implementation. Additionally, it discusses **Models Used in Digital Twins**, focusing on the methodologies that support these technologies.

A dedicated section on **Digital Twin Models Identified in Non-Widening EU-CONEXUS Partners** show initiatives from various partners, emphasizing collaborative efforts in developing digital twin applications. The document concludes with a **Conclusion** that synthesizes the insights presented and reflects on the implications for future research and practice.

Overall, the structured approach of the document facilitates a comprehensive understanding of digital twin technologies, their applications, and the collaborative frameworks necessary for effective knowledge transfer among partners.

3. Built Environment in Digital Twins

The built environment refers to the physical surroundings in which people live, work, and interact, including buildings, infrastructure, and public spaces. In the context of digital twins, the built environment is represented as a digital replica that simulates the real-world properties, conditions, and behaviors of these structures. By integrating data from sensors, IoT devices, and other sources, digital twins of the built environment enable real-time monitoring, predictive maintenance, energy optimization, and enhanced decision-making for managing infrastructure and urban spaces more efficiently. This digital representation allows for better planning, management, and sustainability of cities and buildings.

3.1. Digital Twin Examples in the Built Environment

Structural Design Management

DT can be used to improve the design, construction monitoring and maintenance of structures. In this case, digital twins can be used to create a 3D model of the building and update it using real-time data. This will allow the engineers and managers to simulate, analyze and optimize the design of the structure by making their decisions based on up-to-date data. Currently, the most widely used models for structural design are Building Information Models (BIM) and Computer Aided Design (CAD) models. DT can provide the following depending on the desired output:

- Virtual Construction Sequencing
- Cost and Schedule Optimization
- Condition Assessment
- Predictive Maintenance
- Load and Stress Analysis
- Energy Efficiency and Sustainability
- Structural Performance Over Time

Thus, engineers have a great amount of control over the design and physical performance of the structure.

Energy Design and Energy Management

Digital twins provide a virtual model that can simulate and optimize energy consumption patterns, environmental impact, and the integration of renewable energy sources in a building or infrastructure before physical construction. The focus here is on design optimization to improve energy efficiency. In the planning and design stage of buildings or infrastructure, digital twins can simulate various energy consumption scenarios based on architectural layouts, materials used, building orientation, climate conditions, and occupancy patterns. Thus, energy design and management need to be done in combination with structural design for optimal building performance in terms of both energy and load/stress. Potential usage of DT in Energy design and management are as follows:

- Simulating Energy Consumption in the Design Phase
- Optimizing Building Orientation and Architecture
- Integrating Renewable Energy Sources

- Real-time Energy Monitoring and Control
- Predictive Maintenance of Energy Systems
- Demand Response and Grid Integration
- Carbon Emissions Monitoring

Facility Management

Digital twins are increasingly being used in facility management (FM) to enhance operational efficiency, reduce costs, improve sustainability, and optimize space utilization. By creating a real-time virtual model of a facility, a digital twin helps facility managers monitor, manage, and improve the performance of buildings, equipment, and infrastructure. By integrating real-time data from IoT sensors within a building to continuously monitor environmental conditions, energy usage, equipment status, and occupant behavior, the twin reflects the live status of all building systems, including HVAC, lighting, water systems, and security. For FM, occupancy modeling is especially useful for simulating the behavioral patterns of the occupants in the building to optimize the working space and energy expenditure. Most popular modeling technique used for this is Agent-Based Modelling (ABM). The following can be achieved for FM by using DT:

- Building Performance Monitoring
- Centralized Control of Building Systems
- Space Usage Analytics
- Flexible Space Management
- Asset Tracking and Lifecycle Management
- Energy Optimization
- Occupant Experience and Comfort

Sustainability Management

Digital twins are a powerful tool for sustainability management, helping organizations and cities monitor, optimize, and reduce their environmental impact. From tracking carbon footprints and energy use to optimizing water consumption and waste management, digital twins enable smarter decision-making that drives sustainability goals. By simulating and analyzing the environmental effects of various actions, they support organizations in achieving long-term sustainability while reducing costs and enhancing resilience. Sustainability management is included through each stage of the lifecycle of a building (Design, construction, operation, demolition) thus, a few different modeling techniques and tools are necessary to use digital twins in sustainability management. Different stages require different tools and models to be observed, demonstrated and evaluated. An extensive list of tools is currently used for sustainability management. The following are achieved by using DT in sustainability management:

- Real-time Carbon Emissions Tracking
- Scenario Simulations for Carbon Reduction
- Energy Optimization and Monitoring
- Renewable Energy Integration
- Water Resource Simulation and Management

- Waste Tracking and Management
- Lifecycle Assessment and Circularity
- Smart City Energy and Resource Management
- Traffic and Emission Management
- Environmental Impact Assessment (EIA)

Safety Management

For safety management, digital twins provide a way of simulating different loads and stresses in the built environment to find out the safe operating range. Digital twins track the condition of buildings, bridges, and other infrastructure in real-time. Sensors embedded in structures can monitor stress, strain, temperature, and vibration, which are critical for detecting early signs of wear or potential failure, such as cracks or instability. It is also possible to perform risk assessment and evacuation/hazard procedures by using digital twins. The tools included are usually related to the 3d design aspect of the built environment as well as sensors and IoT devices to collect and connect data in one cloud. The uses of DT in safety management are as follows:

- Real-Time Monitoring and Risk Detection
- Simulation of Emergency Scenarios and Evacuation Plans
- Predictive Maintenance and Inspections
- Resilience and Disaster Recovery
- Occupant Safety and Behavior Tracking
- Energy and Fire Risk Management
- Post-Incident Analysis and Recovery

Smart city/smart building management

A smart building uses its intelligence to collect actionable data from user devices, sensors, systems, and services on the premises. The smart city does the same thing on a larger scale. Digital twins track the performance of HVAC systems, elevators, lighting, and security systems in a building. This enables building managers to monitor operational health, detect potential failures, and schedule preventive maintenance before equipment breaks down, reducing downtime and enhancing safety. In urban environments, digital twins of bridges, roads, water pipes, and other infrastructure assets monitor their condition in real-time. They help predict when maintenance is needed, preventing costly repairs and ensuring public safety. For example, sensors embedded in roads can alert authorities about potholes or structural damage. Currently, the most used models are physics-based, agent and computational fluid dynamics models. The following are the current uses for DT models in safety management

- Real-Time Monitoring and Predictive Maintenance
- Simulation of Urban and Building Environments
- Energy Management and Sustainability
- Improving Public Safety and Security
- Urban Planning and Development
- Sustainability and Environmental Management

Construction Management (refers to the construction stage of a project)

Digital twins are used to transform construction management by providing real-time insights, improving safety, optimizing resources, and enhancing collaboration. DT extends the capabilities of Building Information Modeling (BIM) by integrating real-time data with 3D models. These models evolve with the construction process, allowing teams to visualize changes and updates in real time. The simulation of different construction scenarios is enabled such that various design alternatives, material choices, or construction methods can be tested. Project stakeholders can test and visualize the impact of these decisions before implementation. From design and planning through construction to post-completion facility management, DTs enable better decision-making, reduce risks, and improve overall efficiency. Platforms like Autodesk Forge, Siemens MindSphere, Bentley iTwin, and Trimble Connect are at the forefront of this revolution, making construction projects smarter, safer, and more sustainable. The following are the potential and common uses for DT in construction management.

- Design and Planning Optimization
- Real-Time Monitoring and Progress Tracking
- Predictive Maintenance and Asset Management
- Safety Management and Risk Mitigation
- Project Scheduling and Optimization
- Collaboration and Communication
- Environmental Impact and Sustainability

Transport Management

In transport management, to optimize traffic flow, enhance safety, reduce emissions, and improve overall efficiency. In the context of smart cities, they serve as real-time virtual replicas of transportation systems, such as road networks, rail systems, airports, and public transit. By integrating real-time data from sensors, cameras, and vehicles, digital twins allow authorities and planners to simulate and optimize transportation operations. Thus, transport management can be seen as a subcategory of smart city management. It provides city planners, and logistics operators with a powerful tool to improve safety, efficiency, and sustainability in modern urban and transport systems. Usually, the models used are agent-based models paired with a 3d model for visualization of infrastructure and the roads/pathways. Here are the most common current uses of DT in Transport Management. [1]

- Traffic Flow Optimization
- Public Transportation Management
- Autonomous Vehicles and Smart Mobility
- Rail and Metro System Optimization
- Aviation and Airport Management
- Emergency and Incident Management

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Figure 1. Digital Twin Practices in Built Environment

3.2. Tools Used for Built Environment

In the context of Digital Twins, a tool refers to the technologies, platforms, and software applications used to create, maintain, analyze, and interact with a digital twin. Digital twins are virtual models or simulations that replicate physical objects, systems, or processes in real time, and tools are essential for bridging the gap between the physical and digital worlds. In the built environment, 6 types of tools are used most frequently. These are sensors, IoT devices, data transmission, data storage and processing, simulation and modeling, machine learning and predictive tools.

3.2.1. Sensors

A sensor is a device that detects, measures, and records physical properties from its surrounding environment, converting these properties into readable data that can be processed and analyzed. Sensors can measure a wide range of physical variables, such as temperature, pressure, motion, humidity, light, sound, force, and more. There are several types of sensors used for the creation of digital twins. These include temperature, flow, pressure, vibration, humidity, current, voltage, stress and strain sensors. These sensors collect information on real-time data about physical assets, systems, and environmental conditions. These sensors play a critical role in creating accurate digital representations of energy assets, such as power plants, wind turbines, and electrical grids, by feeding data into digital twin models for monitoring, control, and predictive maintenance. So, sensors are the vital link between the physical and digital worlds in a digital twin system. They enable real-time data collection, which keeps the digital twin up to date, allowing for monitoring, analysis, prediction, and optimization of the physical system or asset. Sensors are also integral parts of IoT devices like smart meters. [2]

3.2.2. IoT Devices

An IoT (Internet of Things) device is a physical device that is embedded with sensors, software, and communication technology, enabling it to collect data from its environment and transmit that data over the Internet or other networks. These devices can range from simple household gadgets like smart thermostats to complex industrial machines that monitor production processes. IoT devices communicate with other devices, systems, or applications, creating a network of connected objects that can share information and work together. In the context of digital twins, IoT devices play a critical role in facilitating real-time data transfer from the physical object, environment, or system to its digital counterpart. They are responsible for providing the data that keeps the digital twin synchronized with its physical counterpart. By embedding IoT devices in physical assets (such as machines, vehicles, or infrastructure), a continuous stream of data is sent to the digital twin, enabling real-time monitoring, analysis, and decision-making.[3]

3.2.3. Data Transmission

A data transmission tool is any technology, protocol, or system used to transfer data from one location to another. This can include a variety of methods, such as wireless communication, wired networks, or cloud-based systems. In the context of digital twins, data transmission tools are crucial for ensuring that the real-time data collected by sensors and IoT devices is reliably transmitted to the digital twin for processing, analysis, and updates. In a digital twin environment, data transmission tools facilitate the flow of information between the physical object (or system) and its virtual counterpart. These tools enable seamless and continuous communication between sensors, IoT devices, edge devices, and the digital twin platform. Data transmission can occur over the internet, through cellular networks (e.g., 4G, 5G), via satellite, or through local networks (e.g., Wi-Fi, Ethernet, or Bluetooth).[4]

3.2.4. Data Storage and Processing

A data storage and processing tool is any system, platform, or technology that enables the collection, organization, management, and analysis of large volumes of data. In the context of digital twins, these tools are critical for storing the vast amounts of data generated by sensors, IoT devices, and other data sources, and for processing this data to extract meaningful insights. In a digital twin environment, data storage and processing tools play a pivotal role in managing the continuous inflow of data from the physical asset or system and enabling real-time analysis, simulations, and decision-making. They ensure that data is securely stored and efficiently processed so that the digital twin can perform its functions, such as monitoring, predicting, and optimizing the behavior of its physical counterpart.[5]

3.2.5. Simulation and Modelling

A simulation and modeling tool is a software application or platform that allows the creation, testing, and analysis of virtual representations (models) of physical objects, systems, or processes. These tools enable users to replicate real-world behaviors in a digital environment, allowing for experimentation and scenario testing without affecting the actual physical system

In a digital twin, simulation and modeling tools serve as the backbone for building, analyzing, and enhancing the virtual representation of a physical object or system. They help in creating a realistic, data-driven model of the asset, which can then be used to simulate real-world conditions, test potential changes, and predict future states. Simulation and modeling tools integrate data from various sources (such as sensors, IoT devices, and historical records) into the digital twin, allowing for dynamic simulations that evolve with the real-time condition of the physical asset.[6]

3.2.6. Machine Learning and Predicting

A machine learning (ML) and predictive tool is a software or platform that uses data-driven algorithms and statistical models to identify patterns, make predictions, and generate insights. These tools learn from historical and real-time data to improve decision-making, automate processes, and anticipate future outcomes. In the context of digital twins, ML and predictive tools are vital for enabling the digital twin to forecast the behavior of physical systems, optimize performance, and detect anomalies. In a digital twin, machine learning models analyze large datasets, which often come from sensors and IoT devices monitoring the physical object. These tools allow digital twins to evolve beyond static representations into intelligent systems capable of self-improvement, predictive maintenance, and real-time optimization. ML and predictive tools continuously refine their models based on new data, allowing the digital twin to improve over time. By using historical and real-time data, digital twins can make accurate predictions about future states, detect potential failures, and suggest optimal strategies for improving performance. [7]

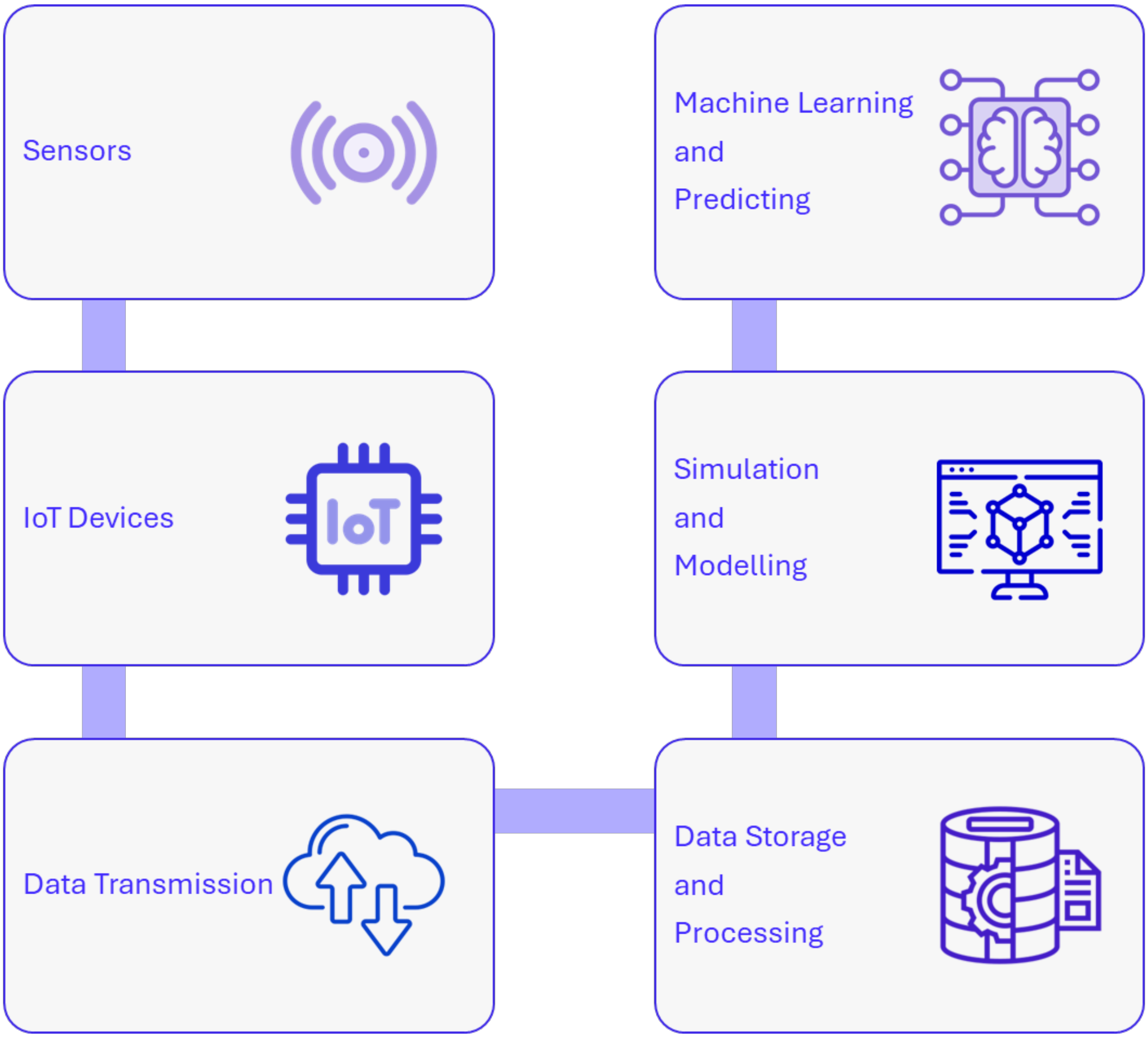

Figure 2. Tools Used for Built Environment

3.3. Case Studies in Built Environment

This section includes digital twin technology used in 4 different case studies in the built environment. The tools used are explained for each case study and a table is presented at the end to visualize the differences and similarities between them.

- **Khatib & Alami, Digital Twin of Muscat (Smart city infrastructure)**

By combining GIS, BIM, predictive analytics, IoT sensors, real-time monitoring, AI, and cloud-based platforms, Khatib & Alami's digital twin for Muscat was designed to provide comprehensive urban management solutions. The digital twin helps improve security, flood preparedness, and overall city infrastructure resilience. Drones were employed to take aerial images of the city to map the geography and the position of the buildings in the city. IoT sensors were employed to enable real-time data collection and monitoring across the city's infrastructure. These sensors provided critical insights into the operations of urban systems such as traffic management, utilities, water networks, and environmental conditions. Esri ArcGIS was used for integration of geographical real-time data into the digital twin. Bentley's LumenRT was then employed to animate the digital twin, enabling simulations such as flooding and day/night cycles for real-world scenario planning, helping the government improve preparedness for climate-related disasters and secure strategic areas. [8]

- **AEGEA, Brazil's Largest Sanitation Map (Sanitation and utilities)**

AEGEA is a leading private company in Brazil's sanitation sector, and it is behind the creation of the country's largest and most comprehensive sanitation map, designed to improve water supply, sewage treatment, and overall sanitation infrastructure. A digital twin of the city and water-based infrastructure was created. The digital twin leverages a digital tool called ContextCapture and Bentleys open modeling tools for processing over 150000 photos and generating a 3D reality mesh. Real-time data is fed into the system using various sensors to detect water level and quality. ContextCapture uses photogrammetry to convert 2D images into 3D models. It processes aerial photos, drone footage, or ground-level images to generate accurate representations of physical environments. ContextCapture models are used within Bentley's iTwin Platform, which is a comprehensive digital twin environment. iTwin allows users to collaborate, analyze, and visualize digital twins in real time, using data generated from ContextCapture models as a baseline. [9][10][11]

- **The Edge, Deloitte HQ, Amsterdam (Smart building and energy efficiency)**

The Edge, Deloitte's headquarters in Amsterdam, is renowned for being one of the world's smartest and most sustainable buildings. The digital twin of The Edge integrates advanced technologies and data-driven methods to manage the building's operations efficiently. The tools used include a wide range of IoT sensors that were embedded throughout the building to capture real-time data on occupancy, temperature, humidity, lighting, and energy consumption. The digital twin is tightly integrated with the Building Management System (BMS), which controls key mechanical and electrical systems such as HVAC (Heating, Ventilation, and Air Conditioning), elevators, and lighting. Siemens Building Automation systems and Schneider Electric's EcoStruxure are the tools used that are designed to optimize energy use and comfort. Data collected from sensors and the BMS is analyzed using advanced analytics and machine learning algorithms. The specific tool used is Microsoft Azure, which acts as the cloud platform for storing and processing the building's data, enabling real-time analytics and historical data analysis. A 3D Building Information Model (BIM) is used to create a digital representation of the physical structure of The Edge. Autodesk's Revit was used for BIM modeling, as it is commonly used for creating architectural and MEP (mechanical, electrical, plumbing) models. To handle the massive data flows generated by the sensors, cloud and edge computing solutions are used to process data efficiently and in real time. Microsoft Azure Cloud is central to The Edge's digital twin for storing, processing, and analyzing large volumes of data. [12]

- **Bristol City Leap Smart Buildings (Energy management for public buildings)**

The Bristol City Leap project is a large-scale initiative aimed at decarbonizing the city of Bristol, UK, by implementing smart building technologies, including digital twins. The digital twin aspect of this project involves creating virtual replicas of municipal buildings to optimize energy use, improve sustainability, and reduce carbon emissions. Sensors used include devices for monitoring energy consumption, environmental conditions (temperature, humidity, air quality), occupancy, and equipment status (e.g., boilers, HVAC units). The digital twin integrates with the building management systems to control critical infrastructure like HVAC, lighting, and electrical systems. Schneider Electric BMS platforms were used that can interface with IoT networks, enabling real-time control and automation. For energy management, platforms like Schneider Electric's EcoStruxure specifically designed to support energy efficiency were used to meet the sustainability goals. 3D BIM is used to create a detailed virtual representation of the building, which includes architectural, structural, and operational data. Autodesk Revit was the tool employed for this function. For cloud computing and edge processing, Microsoft Azure IoT was used where it provides the cloud infrastructure for processing and storing building data. It enables real-time monitoring, predictive maintenance, and historical analysis of building performance. For integration, Microsoft Azure Digital Twins was used as a comprehensive platform that integrates IoT devices, AI models, and BIM data to create a dynamic digital twin for smart buildings. [13]

- **Johnson Controls Headquarters, Shanghai, China (Facility Management)**

The Johnson Controls Headquarters in Shanghai, China is a state-of-the-art smart building that integrates digital twin technology to enhance energy efficiency, sustainability, and occupant comfort. As a global leader in smart buildings and sustainability, Johnson Controls leverages advanced IoT, AI, and machine learning technologies within its headquarters to create a highly connected, data-driven building environment. This digital twin implementation aligns with Johnson Controls' OpenBlue platform, a suite of connected solutions aimed at optimizing building performance and reducing environmental impact. The headquarters is a prime example of how digital twins can contribute to smart building management, sustainability, and energy optimization.

Key Features of the Digital Twin Implementation:

1. **Building Management Optimization**: The digital twin platform monitors and manages various building systems like **HVAC**, **lighting**, **energy consumption**, and **occupant behavior** in real-time. By continuously gathering data from a network of **IoT sensors**, the digital twin creates a dynamic virtual model of the building that helps optimize operations and reduce energy waste.
2. **IoT-Enabled Devices**: The building utilizes an extensive array of **smart sensors** and **IoT devices** to track temperature, humidity, air quality, occupancy, and energy consumption. These devices communicate through **Wi-Fi**, **Zigbee**, and other protocols to a central management system, providing real-time insights into the building's performance.
3. **AI and Machine Learning**: **AI-powered algorithms** are used to predict building energy

demands, optimize resource consumption, and schedule predictive maintenance. By analyzing historical data and forecasting patterns of use, the digital twin can adjust HVAC, lighting, and other systems proactively, reducing operational costs and improving sustainability.

4. **Energy Efficiency and Sustainability**: One of the main goals of the digital twin is to enhance **energy efficiency**. By simulating different operational scenarios, the twin enables energy savings by optimizing system performance in response to external factors like weather and internal factors like occupancy.

5. **Occupant Comfort**: Through **real-time occupancy sensing** and predictive algorithms, the building automatically adjusts temperature, lighting, and air quality to ensure optimal comfort for occupants while minimizing unnecessary energy use.

6. **Edge and Cloud Computing**: Data collected from IoT devices is processed using a combination of **edge computing** for immediate, local responses and **cloud computing** for large-scale data analysis and predictive modeling. [14]

- **Siemensstadt 2.0, Berlin, Germany (Smart City Management)**

Siemensstadt 2.0 in Berlin, Germany is an ambitious smart city project initiated by Siemens, transforming the historic Siemensstadt district into a modern urban innovation hub. The project, spanning over 70 hectares, integrates digital twin technology, IoT, and AI to create a connected and sustainable living environment. Siemensstadt 2.0 is envisioned as a center for smart industry, education, and research, while promoting green technologies and energy efficiency.

For the creation of a digital twin, Siemensstadt 2.0 utilizes tools like Siemens MindSphere, a cloud-based IoT operating system, for gathering and analyzing data from a vast network of sensors and IoT devices. Building Information Modeling (BIM) is used to develop detailed digital representations of buildings and infrastructure, allowing for simulations of energy usage and urban planning. Edge computing ensures real-time data processing at the source, minimizing latency in decision-making, while AI-driven predictive analytics help optimize the performance of energy grids and building management systems by anticipating future demands and failures. This combination of advanced tools enables the creation of dynamic, responsive models that support the sustainable management of Siemensstadt. [15, 16].

- **Forth Bridges Digital Twin Project, Scotland (Smart City Infrastructure)**

The Forth Bridges Digital Twin Project is a Scottish initiative that creates a digital replica of the three iconic Forth bridges—Forth Rail Bridge, Forth Road Bridge, and Queensferry Crossing. This digital twin uses advanced 3D modeling and sensor data to mirror the real-time conditions of the bridges, allowing for efficient monitoring, predictive maintenance, and improved safety management. By simulating structural responses to environmental factors like weather and traffic, the project enhances infrastructure management, reduces operational costs, and supports the longevity and resilience of these critical transport links.

The Forth Bridges Digital Twin Project employs a sophisticated array of tools for creating a detailed and functional digital twin. The use of advanced sensors (e.g., strain gauges, accelerometers), IoT platforms (like Libelium Waspmote), and data transmission technologies (5G, LoRaWAN) ensures real-time monitoring. Data storage and processing take place in Microsoft Azure, while simulation and modeling tools like Autodesk InfraWorks and ANSYS allow detailed simulations. Finally, predictive maintenance is powered by machine learning and AI tools such as TensorFlow and Azure Machine Learning, providing a comprehensive digital twin solution for ensuring the long-term safety and functionality of the bridges. [17, 18]

- **Ezhou Huahu International Airport (Construction Management)**

China utilized Bentley Systems' iTwin platform and BIM technology to create a comprehensive digital twin. This project had to manage 25 million model components and multiple stakeholders across various disciplines. The digital twin facilitated efficient collaboration, reducing delivery times by 90 days and saving $12 million. By integrating real-time data and workflows, the digital twin improved productivity by 25% and solved thousands of operational issues, which saved an additional $300 million. This helped in achieving lifecycle management and optimized project coordination and execution.

The digital twin for Ezhou Huahu International Airport was developed using Bentley Systems' tools, specifically the iTwin Platform for integrating massive datasets, including 25 million model components. This platform allowed for a cohesive, real-time collaborative environment that managed the airport's lifecycle from design to operation. OpenRoads was used for professional modeling, ProStructures for structural coordination, and Navigator to ensure seamless collaboration with on-site teams. Together, these tools streamlined multi-source data handling, reduced model delivery times by 90 days, and enhanced productivity by 25%, allowing the team to address thousands of coordination issues and save approximately $300 million [19, 20].

- **Digital Twin Setup in the Roma Termini Railway Station (Safety Management)**

The case study focuses on developing a simulation-based digital twin (DT) for Roma Termini railway station to enhance pedestrian safety and crowd management. This DT leverages real-time data from IoT-enabled devices like security gates, escalators, and ticket machines, integrating them through a Station Management System (SEM) that collects and processes live data. Using AnyLogic software, the DT simulates pedestrian flows, predicts congestion, and provides early warnings and evacuation recommendations. It dynamically adjusts to real-world conditions, enabling proactive decision-making for station managers to manage crowd safety effectively, optimize gate configurations, and allocate resources based on crowd density and flow patterns. [21]

Sensors and IoT Devices: The system utilizes security gates, escalators, and ticket machines as IoT-enabled devices to gather data on passenger flows and asset status. The Station Management System (SEM) integrates these physical assets, providing data on gate status, escalator functionality, and platform occupancy.

Data Transmission: The system leverages RESTful APIs and WebSockets to facilitate data exchange, using formats such as JSON, XML, RDF, and CSV to standardize communication across the station's digital and physical components.

Data Storage and Processing: A Data Integration Middleware layer aggregates and processes data from various station systems, ensuring interoperability between the simulation engine, incident management, and operational management systems.

Simulation and Modelling: AnyLogic is the primary tool for simulation, used here for crowd modeling and congestion prediction. AnyLogic's Pedestrian Library, Process Modeling Library, and Agent-based Modeling Library enable detailed simulation of pedestrian flows and interactions, reflecting real-world crowd dynamics.

Machine Learning and Prediction: Although traditional machine learning is not employed for prediction, AnyLogic's simulation capabilities incorporate real-time updates from SEM. This integration allows the digital twin to dynamically adjust predictions based on current crowd conditions, effectively providing proactive safety insights.

3.4. Comparison of Case Studies

Case Study	Johnson Controls Headquarters, Shanghai, China	Siemensstadt 2.0, Berlin, Germany	Forth Bridges Digital Twin Project, Scotland	Ezhou Huahu International Airport, China
Sensors	Occupancy, Temperature, Humidity, Air Quality, Lighting	Humidity, Temperature, Lighting, Gas, CO2	Strain gauges, Accelerometer, Anemometer, Temperature, Load	Laser Scanners and LiDAR, GPS and Geolocation Sensors, temperature, humidity sensors
IoT Devices	Smart HVAC Systems, Smart Lighting, Energy Meters	Smart HVAC Systems, Smart Lighting Systems, Connected Mobility Devices	Libelium Waspmote IoT platform, Cisco IoT gateways	Smart Wearables, GPS Trackers, Drones
Data Transmission	Wi-Fi and Ethernet Networks, igbee and Bluetooth Low Energy, Building Automation Systems (BAS) Protocols	5G Networks, LoRaWAN Protocol, Wi-Fi and Ethernet Networks	5G and LoRaWAN, Fiber-optic networks	LoRaWAN, Wi-Fi amd Bluetooth.
Data Storage and Processing	Cloud Computing (Microsoft Azure), Edge Computing	Cloud Computing (Siemens MindSphere),	HBM (Hottinger Baldwin Messtechnik), Microsoft Azure Cloud, Azure Data Lake	Azure Blob Storage, Data Lake, AWS Kinesis and Azure Stream Analytics
Simulation and Modelling	Building Information Modeling (BIM) by Autodesk Revit, EnergyPlus or TRNSYS for energy flow simulation	Building Information Modeling (BIM), Energy Modeling Software (Siemens PSS® SINCAL and EnergyPlus)	Building Information Modeling (BIM), Autodesk InfraWorks, Bentley Systems ContextCapture	OpenRoads, ProStructures,
Machine Learning and Prediction	OpenBlue AI Platform	Siemens MindSphere	IBM Watson IoT Platform, Microsoft Azure Machine Learning	TensorFlow or PyTorch

Tabel 1. Illustrates the tools and methods used in Johnson Controls Headquarters, Shanghai, China Siemensstadt 2.0, Berlin, Germany Forth Bridges Digital Twin Project, Scotland Ezhou Huahu International Airport, China.

Sensors & IoT: Johnson Controls uses its OpenBlue suite with extensive HVAC and security sensors to optimize indoor air quality and energy use. Siemensstadt employs a network of sensors for urban-level insights into energy, mobility, and sustainability, incorporating IoT to monitor environmental and urban conditions. For Forth Bridges, sensors track structural integrity, including stress and weather data to manage bridge health and safety. Ezhou Huahu Airport integrates sensors for real-time logistics and operational monitoring, essential for managing high-traffic airports.

Data Transmission & Storage: Both Johnson Controls and Siemensstadt rely on cloud-based solutions. OpenBlue's real-time platform provides Johnson Controls with continuous updates, while Siemensstadt leverages Siemens' cloud to centralize smart city data. The Forth Bridges project uses a cloud system by Digital Catapult for ongoing structural health, and Ezhou Airport combines edge and cloud storage for rapid data access and storage.

Modeling & Simulation: Siemensstadt incorporates simulations for urban planning to design eco-friendly structures and predict energy needs. Forth Bridges uses a digital model for predictive maintenance on bridge conditions. Johnson Controls uses simulation within OpenBlue for energy and space utilization, while Ezhou Airport models flight and passenger flow to maintain efficient airport operations.

Machine Learning & Prediction: Machine learning in OpenBlue at Johnson Controls supports predictive maintenance and adaptive environment management. Siemensstadt applies AI-driven analytics to anticipate urban resource demands, and Forth Bridges uses AI to predict maintenance needs, ensuring infrastructure safety. Ezhou Airport applies AI to manage logistical workflows, predicting peak times and optimizing passenger processing.

Case Study	Khatib & Alami, Digital Twin of Muscat0	AEGEA, Brazil's Largest Sanitation Map	The Edge, Deloitte HQ, Amsterdam	Bristol City Leap Smart Buildings
Sensors	Cameras, Motion Detectors, Air Quality and Weather, Electricity, Water	Smart Water Meter, Flow, Water Quality, Pressure	Occupancy, HVAC, Light, Temperature, Humidity, Motion	Energy Usage, Air Quality, Temperature, Energy Consumption, CO2
IoT Devices	Smart city sensors for real-time urban data collection, Smart meters for utilities	Smart sanitation monitoring systems, Water flow monitoring and leakage detection meters	Smart meters for building management and control systems, Devices for lighting, HVAC, and occupancy tracking	Smart meters for real-time energy monitoring in buildings, IoT-enabled thermostats, smart lighting
Data Transmission	Cellular, Wi-Fi, LoRaWAN for low-power, long-range transmission for	LoRaWAN, cellular networks for cloud-based transmission	Wi-Fi, Bluetooth, Zigbee for cloud-based transmission	Wi-Fi, LoRaWAN, cellular networks for cloud-based transmission

Case Study	Khatib & Alami, Digital Twin of Muscat0	AEGEA, Brazil's Largest Sanitation Map	The Edge, Deloitte HQ, Amsterdam	Bristol City Leap Smart Buildings
	cloud-based transmission			
Data Storage and Processing	Cloud storage (AWS, Azure) for localized databases for infrastructure metadata	Cloud storage systems for vast datasets (Azure) for High-volume, high-precision databases for asset data	Cloud storage systems for vast datasets (Azure) for High-volume, high-precision databases for asset data	Cloud-based storage integrated with smart building systems
Simulation and Modelling	Esri ArcGIS for urban planning simulations and models	Bentley ContextCapture for 3D modeling and Virtual reality (VR) for asset lifecycle management	Autodesk Revit for BIM, Siemens Building Automation system for energy simulation and modelling	Autodesk Revit for BIM, Schneider Electric's EcoStruxure for energy simulation platforms for forecasting and optimization
Machine Learning and Prediction	AI algorithms for predictive maintenance (Python, MATLAB)	Machine learning for water loss detection and network optimization (Python, MATLAB)	Machine learning for energy efficiency (Python, MATLAB)	AI for predicting energy demand and optimizing building systems (Python, MATLAB)

Tabel 2. Illustrates the tools and methods used in Khatib & Alami, Digital Twin of Muscat AEGEA, Brazil's Largest Sanitation Map, The Edge, Deloitte HQ, Amsterdam, Bristol City Leap Smart Buildings.

Sensors and IoT Devices: All projects heavily rely on IoT sensors for real-time data collection. Khatib & Alami and AEGEA focus on urban and utility infrastructure, while The Edge and Bristol City Leap focus more on building and energy management.

Data Transmission: Across all projects, **Wi-Fi** and **cellular networks** are essential for data transmission. Low-power networks like **LoRaWAN** are used in Bristol and AEGEA for long-range and energy-efficient transmission.

Data Storage and Processing: Cloud storage and processing are critical across the board, with **AWS**, **Azure**, and other cloud platforms used to manage vast datasets in real time.

Simulation Tools: 3D modeling tools such as **Bentley ContextCapture** and **Autodesk Revit** for **BIM** are used for simulating infrastructure and building management. These simulations optimize urban planning in Muscat, energy efficiency in Edge and sanitation infrastructure in Brazil.

Machine Learning and Prediction: AI and machine learning are applied for predictive maintenance and energy optimization. In Bristol and Edge these techniques are particularly focused on energy forecasting and efficiency, while in AEGEA, they help identify water loss and optimize sanitation services.

4. Agriculture in Digital Twins

In the context of digital twins, agriculture refers to the use of digital replicas to simulate and monitor farming systems, crops, and livestock. By integrating data from sensors, weather forecasts, soil conditions, and machinery, digital twins enable farmers to optimize crop yields, manage resources efficiently, and predict future outcomes. These digital models help improve decision-making in areas like irrigation, pest control, and fertilizer application, leading to more sustainable and productive farming practices. Ultimately, digital twins in agriculture enhance the precision and efficiency of operations, contributing to smarter farming and better management of agricultural ecosystems.

Smart agriculture (SA), the increasing use of information technologies, sensors, autonomous vehicles, data analytics, predictive modeling, and other digital technologies related to agricultural activities – has been strongly argued for to significantly contribute to increased food security, reduced water consumption, reduced fertilizer and pesticide input, and increased farm profitability. Despite this, the adoption rate of smart agricultural technologies is still low and varies significantly according to the specific technology and the geographical area considered [22]. Smart farming consequently is a comprehensive approach to agriculture that utilizes a diverse range of technologies. It is necessary to integrate tools such as the Internet of Things, artificial intelligence, and automation. When we talk about automation, we need to understand all the processes in a complex agroecosystem. A SA creates a sophisticated and interconnected farming ecosystem. Precision agriculture (PA) is a subset of SA. In a broader sense (PA) is a farm management approach that necessarily leans on use of digital techniques with a specific focus on monitoring and optimizing agricultural production processes.

To better monitor the inclusion of digital twins (DTs) in smart agriculture with a contribution towards its sustainability, it is necessary to distinguish the development of agriculture from its beginnings to the current stage through an approach from agriculture 1.0 to 5.0. (R)evolution of agricultural activities in developed countries, which encompasses all the major technological innovations is listed below:

- Agriculture 1.0 (until 1920): manual workforce and animal traction.
- Agriculture 2.0 (1920–1960): motorization, introduction and dissemination of tractor innovations (diesel engine, three-point hitch, tires), but manual workforce still prominent;
- Agriculture 3.0 (1960–1980): mechanization, improvement of tractors (higher power, operating machines for all production activities), improvements in genetics, rapid replacement of the manual workforce;
- Agriculture 4.0 (precision agriculture) (1980–2000): improvement of operating machines, greater attention to the human-machine relationship (safety and ergonomics), the introduction of on-board electronic control systems in tractors, first attempts of digitized/computerized management of the farm (never fully and widely consolidated, except in specific sectors such as zootechnics);
- Agriculture 5.0 (smart agriculture) (after 2000): consolidation of electronics and automation (in mobile user-point processes), diffusion of sensors for monitoring activities and on-board positioning systems in tractors, communication protocols between different devices, in-silico simulations for gene modeling and traceability, deep learning to increase agricultural productivity [22].

Agriculture 5.0 therefore throws consolidation of electronics and, sensors for monitoring activities and on-board positioning systems, communication protocols between different devices, here a new perspective opens up, and that is how, based on known automated processes and collected large amounts of data, an environment can be created in which predictions or future events (e.g. due to climate extremes) could be simulated and prevented by decision-makers. A digital twins approach can be the next step in developing SA as an Agriculture 5.0.

Digital twins provide previously unheard levels of control over physical entities and help to manage complex systems by integrating an array of technologies. Recently, agriculture has seen several technological advancements, but it is still unclear if this community is trying to adopt digital twins in its operations [23].

Digital Twins serve as virtual counterparts, replicating the characteristics and functionalities of tangible objects, processes, or systems within the digital space, leveraging their capability to simulate and forecast real-world behavior [24]. This advanced digital technology has found different applications in SF, facilitating a comprehensive virtual replica of a farm. It can adapt and encompass vital aspects such as: soil composition, weather conditions, crop cultivation measures, crop developing vegetation phases. By joining data from diverse sources: soil, plant conditions, environmental and meteorological sensor networks and high-resolution UAV and Satellite imagery, farmers gain access to dynamic and up-to-date visualization of their agricultural domains. All this empowers them to make well-informed and timely decision making. Farmers are more reliable in their soil conditions, irrigation plans, optimal fertilization methods, and other cultivation measures, then effective pest management strategies, all this is for the purpose of enhancing overall farm productivity and sustainability.

As virtual replicas of physical objects or systems, DTs represent a highly promising advancement in this field. In SA, digital twins enable agriculture experts, researchers, and farmers to simulate various scenarios, test different strategies, and predict outcomes accurately. DTs in smart farming offer transformative possibilities, revolutionizing crop cultivation and management while enabling optimization of resource utilization, minimizing environmental footprint, and enhancing crop yields for a sustainable and efficient agricultural ecosystem [25]. In this context, the DT is uniquely positioned to overcome these challenges and support the goals of sustainability. Through the use of state-of-the-art technologies, increased information availability can empower stakeholders to pursue sustainable objectives and production methods [26]. A DT can provide the following depending on the desired output.

- Real-time monitoring and Predictive Maintenance (soil performance, weather influence, agriculture measures implementing, culture development, harvest and post-harvest maintenance)
- Sustainability and Environmental Management (biodiversity, soil fertility, environmental pollution/degradation)
- Safety Management and Risk Mitigation (food safety, work safety, farmer's welfare, etc.)
- Project Scheduling and Optimization (decision support and socio-economic welfare of farmers, farms and rural areas)
- Collaboration and Communication (improvements in responses to the demanding administrative and development component of the common EU agricultural policy).
- DT can provide the following depending on the desired output.

The key components and interactions of DT in agriculture, important for their role in data collection, preprocessing, modeling, simulation, analytics, decision support, visualization, and control, with aim in optimizing farm operations and improving decision-making processes are: technology for creating reality, artificial intelligence (AI), communication technologies, the connection between the real twin and the DT, distributed Ledger Technologies (DLT) and Blockchain, cloud, IoT, simulating software.

- **Technology for creating reality**

DTs rely on augmented (AR), virtual (VR), and mixed-reality (MR) technologies. As an example, they can be created using three-dimensional (3D) technologies and presented as holograms or experienced through AR/VR/MR devices, such as the Microsoft HoloLens. Using sensors installed in the field, their real-time digital twin can be generated and projected as a hologram in remote locations. This enables individuals in different locations to engage in interactions that simulate being physically present in the same space [27].

- **Artificial Intelligence**

Artificial Intelligence (AI) integration into physical assets that lack it inherently is a key advantage of DTs. This introduces a specialized intelligence capable of efficiently comprehending vast amounts of numerical data and deriving domain-specific insights faster than human experts. Consequently, the data obtained from the digital twin's surroundings and physical counterpart should lead to valuable and actionable conclusions [28].

- **Communication Technologies and Schemes**

DTs rely on communication technologies and schemes to facilitate interaction with the environment, their physical twins, and other DTs on a real-time basis. Effective communication must occasionally occur within a millisecond (ms) timeframe. This is particularly significant in the realm of wireless communication. A necessitating compliance with 5G and tactile internet standards is needed. Then another need for stringent communication standards, lead to a growing demand for repeatable and cost-effective verification procedures [24].

- **Reliability, Integrity, and Credibility**

Reliability, integrity, and credibility are pivotal when DTs are entrusted with sensitive tasks involving transaction management with their real counterparts. It becomes imperative for the real twin to establish a sense of trust in their DT's capabilities and actions. Building and maintaining a solid connection between the real twin and the DT is crucial to fostering effective collaboration, enabling reliable decision-making, and ensuring secure interactions. Consequently, a strong foundation of trust becomes indispensable for the successful operation and advancement of DT-enabled systems [29].

- **Distributed Ledger Technologies and Blockchain**

In recent times, Distributed Ledger Technologies (DLT), such as blockchain [30], have emerged to add to user authentication and data integrity regarding data sharing. To unlock its full potential and achieve its envisioned advantages, addressing outstanding concerns surrounding the technology is imperative. DLT offers a decentralized approach that eliminates the need for a central authority or database, distinguishing it from traditional data-sharing methods [30].

- **Cloud Computing**

Cloud computing presents a valuable opportunity for DTs to enhance their scalability and availability, assisting their real twins anytime and anywhere. By leveraging cloud computing infrastructures, computation and control tasks can be offloaded from the local environment to remote servers, enabling DTs to handle complex processes and ensure seamless availability efficiently. The scalability of DTs is significantly improved through cloud computing, as the computational resources can be dynamically allocated and scaled based on demand [24].

- **Internet of Things**

Internet of Things (IoT) with 5G and the Tactile Internet (TI) entity meanings have emerged as ground-breaking technologies, ushering in a new era of communication with their focus on ultra-high reliability and ultra-low latency. The Tactile Internet (TI) is an emerging area of research involving 5G and beyond (B5G) communications to enable real-time interaction of haptic data over the Internet between tactile ends, with audio-visual data as feedback. This shift in communication paradigms from content-oriented to control-oriented is especially significant for applications that involve human-in-the-loop interactions, demanding minimal delays and seamless integration of communication and control mechanisms as demanded in DT infrastructure [24].

- **Modelling and Simulation Software**

A DT could be addressed as a tight combination of (1) an object model, in conjunction with (2) an expansive set of data that is directly following the object that may evolve, and finally, (3) a method for modifying and refining the model based on the available data [31]. The experts decide the need and selection of the training, validation and verification data concerning specific case studies, types of soil, plant types, leaf area, plant height, regarding the Physical Twin, or technological use cases [24, 31].

4.1. Digital Twin Examples in Agriculture

Growth Prediction/Optimization

The first way to apply DTs in agriculture is to create a crop DT, which can for example predict growth or yield (Laryukhin et al. 2019). Skobelev et al. (2020) integrated the ability to adapt to changing environmental conditions. Decision support is another topic that works as DTs (Moghadam et al. 2020). The “Digital Potato” is a tool with which a potato harvester can be adjusted so that the potatoes are not damaged during harvesting (Kampker et al. 2019). In addition, Barnard (2019) created a digital twin of an indoor garden that calculates the ideal conditions for plants to grow. It uses the data gathered by a gardening robot such as humidity and nutrient content of the soil as well as simulations to determine what the robot has to do to ensure that each plant gets exactly the right quantity of nutrients and water it needs for ideal growth. The data gathered, the algorithms and the digital twin itself are saved in the cloud.

- Environmental adaptation
- Growth time and efficiency prediction
- Damage Prevention
- Harvest Efficiency
- Nutrition optimization

Water Quality Management

DTs can be used in aquaculture or aquaponics for monitoring water quality (Niswar et al. 2018; Ahmed et al. 2019). In aquaculture and aquaponics, digital twins are used to monitor water quality by integrating real-time data from various sensors placed in water tanks or systems. These sensors measure critical parameters such as temperature, pH levels, dissolved oxygen, salinity, and ammonia concentrations, which are essential for maintaining a healthy environment for aquatic life. The digital twin model simulates and visualizes these conditions in real-time, allowing for continuous monitoring and early detection of potential issues. By leveraging data-driven insights, farmers can optimize water quality, adjust filtration systems, and ensure the health of both fish and plants in aquaponic systems, leading to more sustainable and efficient operations.

- Predict water quality changes
- Simulate water conditions
- Optimize filtration and aeration systems
- Track long-term water quality
- Detect potential danger signs

Livestock Wellbeing

Another study used a DT for the well-being of livestock by controlling the conditions in a barn (Jo et al. 2018). DTs can also be used for vertical farming (Monteiro et al. 2018). DTs can also be used in urban areas. They were used for monitoring an underground urban farm and for urban beekeeping (Jans-Singh et al. 2020; Johannsen et al. 2021). Another application was the digital twin of a cow that makes predictions for heat, estrus and health according to its behavior. It is working based on data from a pedometer attached to the cow as well as company provided location services that accurately detect the cow's movement Kruize (2018).

- Environmental condition monitoring
- Improve animal health
- Enhance comfort
- Predict health risks
- Optimize breeding
- Monitor behavior
- Support herd management

Unmanned Ground Vehicles

Tsolakis et al. (2019) created a digital twin to emulate the use of unmanned ground vehicles in fields. It accepts the actual landscape of a field as input by utilizing digital elevation models retrieved from Open Street Maps. It recreates the 3D model of the field along with possible additions like trees and static objects. It contains a predefined selection of commercially available unmanned ground vehicles which a farmer can test on the virtual field to find the most efficient for their case.

- Emulate vehicle operation

- Create Field Models
- Optimize UGV selection
- Improve operational efficiency
- Enhances decision making

Stock Balance for Self-Contained Environment

Tan et al. (2019) used a digital twin of a self-contained aquaponics production unit. The purpose of this digital twin is to balance the fish stock and plants in the unit by monitoring them and controlling the unit automatically. The digital twin uses temperature, light intensity, water flow, pH and dissolved salts sensed data. The virtual unit performs simulations of fish feed, fish weight gain, pH, nitrates and plant growth as what-if scenarios to find optimizations on the behavior of the whole system. It does this for production maximization, waste minimization, water conservation, meeting quality standards and other production goals. In their work, Machl et al. (2019) used a digital twin of the cultivated landscape to support planners in designing agricultural road networks. The digital twin finds the road network segments with high relevance for agricultural transportation helping planners to modernize these segments according to the agricultural needs. The digital twin creates an information model (described as a UML class) by coupling spatiotemporal information of the cultivated landscape with complex analytical methods.

- Optimizing production goal
- Simulating system response
- Improving system efficiency
- Simulating environmental conditions

4.2. Tools Used for Digital Twins in Agriculture

4.2.1. Sensors

In agriculture, sensors are vital for gathering real-time data from the field. These sensors measure various parameters such as soil moisture, temperature, pH, and nutrient levels. Soil moisture sensors, for example, help farmers determine when to irrigate crops, ensuring water is used efficiently. Temperature and pH sensors monitor soil health, which is critical for optimizing crop growth. Other sensors can also track weather conditions like rainfall and humidity, providing farmers with insights to make more informed decisions about planting, harvesting, and pest management.

4.2.2. IoT devices

IoT devices in agriculture enable the seamless transmission of data collected by sensors to central systems for monitoring and analysis. These devices connect sensors on the field with cloud platforms, allowing farmers to access real-time data remotely via smartphones or computers. For instance, smart irrigation systems powered by IoT devices can automatically adjust watering schedules based on soil moisture levels, optimizing water usage and reducing waste. IoT devices also help in monitoring environmental factors, like temperature and humidity, in greenhouses, improving the overall efficiency of farming operations.

4.2.3. Data Transmission

In agriculture, data transmission is essential for ensuring that data collected from various sensors and IoT devices reaches the central storage or processing systems. Technologies like cellular networks, Wi-Fi, and LoRaWAN are commonly used to transmit data from the field to cloud platforms or local data hubs. These systems enable the remote monitoring of crops and soil conditions, even in remote areas. By ensuring reliable data transmission, farmers can make timely decisions based on real-time information, whether it's adjusting irrigation schedules or responding to changing weather patterns.

4.2.4. Data Storage and Processing

Data storage and processing systems are fundamental in agriculture to manage the large volumes of data generated by sensors and IoT devices. Cloud-based platforms are often used to store this data securely, enabling farmers to access and analyze it from anywhere. Advanced data processing techniques help convert raw data into actionable insights, such as predicting crop yields, identifying potential pests, or determining optimal planting times. By efficiently managing and processing agricultural data, farmers can improve operational efficiency and make more informed decisions about crop management and resource allocation.

4.2.5. Simulation and Modelling

Simulation and modeling tools are used in agriculture to predict and optimize farming practices. These models simulate various environmental conditions and their effects on crops, such as predicting the impact of weather, soil quality, and irrigation methods on crop yield. Using these tools, farmers can test different scenarios, such as adjusting irrigation schedules or planting different crop varieties, to determine the most effective strategies for maximizing yield and reducing resource waste. Simulation helps in making data-driven decisions that can improve productivity while minimizing environmental impact.

4.2.6. Machine Learning and Prediction

Machine learning and prediction technologies in agriculture are used to analyze data and predict future trends or potential issues. For example, machine learning algorithms can predict crop yields based on factors such as soil conditions, weather patterns, and historical data. Predictive models can also help identify the likelihood of pests or diseases before they affect crops, enabling early intervention. Additionally, machine learning can optimize irrigation schedules, forecast fertilizer needs, and assist in precision farming by providing data-driven insights that improve crop management and resource efficiency. (Saiz-Rubio et al. 2020).(Purcell and Neubauer 2023). (Martos et al. 2021). (Catala-Roman et al. 2024). Catala-Roman et al. (2024) chose OpenDroneMap to be the best software, because of its best quality-to-features ratio and its low cost-benefit ratio.

4.3. Case Studies in Agriculture

DT in sustainable agriculture are according to many authors [22, 23, 24] in primary stages and are not developed enough to offer all the benefits that other human activity areas (building, energetic sector etc.) enjoy. Exceptions included some deployed applications that were part of a European Union-funded program [23]. There is still a long way to go before the agricultural community can fully rely on the benefits of DT. Agricultural researchers and stakeholders should make an effort to stay up to date with technological advancements and seek to find links between agricultural problems, and problems that are solved with DT in other disciplines [23]. But scientific reviews mostly describe: plant nutrition or crop development as the most interesting and already adjusted to get first DT solutions. It is a subset in the sense of precision agriculture, but more broadly we see it as a SA solution for the whole farm, due to the complexity DT will be around for a long time in what we hope is a nearer but certainly some kind of future in sustainable agriculture. An example of a case study for nitrogen (N) fertilization described has wider importance [23].

The importance of the environmental issues associated with N management in crops, has been known for a long time. The productivity of plants is strongly dependent on the availability of N, but crop use efficiency of N is low and can result in significant N releases to the environment. This is an environmental, farmer and food safety issue, and has large administrative and policy-making effort. The N fertilization of crops has seen a growth trend. The impact of fertilizer-derived N, is associated with water pollution and the release of greenhouse gases in major crop-producing regions of the world [32], There is a clear requirement for a more innovative approach to optimize efficient crop N-fertilization and restrict N loss to the environment, made more urgent with the need for an agriculture transition towards greater environmental, economic, and social sustainability [23].

The case study considers tools such as: global positioning systems (GPS), geographic information systems (GIS) and remote sensing (RS), yield monitoring, and soil performance parameters as provided data to build up a reasonably accurate picture of spatial area variability. For a more detailed representation of the area/field (a precondition to the evaluation and potentially varying application of N), the cultivated surface can be divided into more uniform management zones by using the overlay of various thematic maps such as the spatial variability of area, soil properties, crop growth and yield [23].

When the potential management scenarios and their uncertainty are available, the farmer can implement the most sustainable management practice based on both an economic and environmental standpoint, which may include tradeoffs between net revenue and environmental outcomes such as nitrate leaching [33]. As an example, if a digital twin (i.e., a validated crop simulation model) using past observed weather data determines that in 24 out of the last 30 years (80%) a fertilization rate of 150 kg N/ha gives a yield of 10Mg/ha, the farmer may choose to apply 150 kg N/ ha knowing that there is a 20% possibility (6 years out of 30) that applying a higher N fertilization rate would (statistically) result in a higher yield [23].

In conclusion, the DT technology will hardly be able to cover the entire agricultural production on one farm or in one agro-ecosystem, so it is necessary to consider which concept of the application of DT in agriculture we are talking about. In [23] authors arrange till now published papers in seven (28) groups. They are as follows: Energy consumption analysis (analyze the energy consumption of the physical system and find ways to minimize it); System failure analysis and prediction (analyze the data coming from a system to identify the source of failure or when the system is going to need maintenance); Optimization/update (find the optimal parameters for the operation of a system and update it to run with those parameters); Behavior analysis/user operation guide (analyze human-made operations and provide feedback); Technology integration (bring together different already deployed technologies under the same umbrella to control and visualize operations more easily); Virtual maintenance (allow users to virtually test different maintenance strategies to find the least intrusive one) [23].

- **LDAS-MV**

The LDAS-MV project in Mecklenburg Western Pomerania focuses on refining agricultural yield forecasts and managing the water cycle. Leveraging data assimilation techniques within a digital twin framework, it integrates land surface models, satellite remote sensing data, and near-seasonal weather predictions. This fusion allows for the accurate prediction of sub-daily surface conditions, facilitating informed decision-making for agricultural management practices and water resource allocation.

- **NATURE-DEMO**

The NATURE-DEMO project, in which University of Rostock was involved, aims to enhance sustainable infrastructure development by integrating advanced digital twin technologies, specifically within alpine areas, with a focus on methods transferable to coastal environments. The core intention of the project is to create accurate digital replicas of both built infrastructure and their natural surroundings using graph neural network (GNN) models. These digital twins facilitate better planning and management by automating the development and refinement of sustainable building designs and environmental models. By leveraging GNNs, the project seeks to capture complex causal relationships within the infrastructure and environmental systems, enabling more precise predictions and decision-making. The digital twins incorporate data from various sources, including remote sensing and high-precision 3D measurement systems, to monitor and optimize operations, thus contributing to the sustainability and resilience of infrastructure against climate threats such as water stress, floods, and droughts.

Implementing digital twin technology within the NATURE-DEMO project involves several significant challenges. One primary challenge is automating the configuration of GNN models to accurately reflect the causal structures of real-world systems, as opposed to merely identifying correlations. This requires sophisticated methodologies for deriving semantic models from diverse data sources to ensure the digital twins are both accurate and useful. Another challenge is the integration of data from different sources into cohesive graph models, which is essential for effective behavior predictions and actionable insights. Processing and managing large datasets necessitate advanced IT infrastructure and expertise, particularly in developing and deploying AI models. Additionally, the ongoing development and validation of the digital twins against real-world measurements require rigorous control measurements and continuous refinement, adding complexity and demanding a high level of precision and expertise. Addressing these challenges is crucial for leveraging the full potential of digital twin technology in promoting sustainable infrastructure development and environmental protection.

5. Life Sciences and Medical Applications in Digital Twins

In the context of digital twins, life sciences and medical applications involve creating virtual replicas of biological systems, organs, or patients to simulate, monitor, and analyze their health and behaviors. These digital models integrate data from medical imaging, patient records, wearables, and genetic information to enable personalized treatment, disease prediction, and surgical planning. Digital twins in healthcare can help optimize clinical outcomes by providing real-time insights into patient conditions, predicting disease progression, and testing treatment strategies in a risk-free virtual environment. This approach enhances precision medicine, improves patient care, and accelerates medical research and development.

5.1. Digital Twin Examples in Life Sciences and Medical Applications

Personalized Healthcare Models

Digital twins are used to create virtual models of individual patients by integrating medical data such as genetic information, medical history, and real-time health data (e.g., from wearables). These models help healthcare providers tailor treatments and interventions to the specific needs of each patient, improving outcomes and minimizing side effects.

- Tailored treatment
- Minimized side effects
- Faster Diagnosis
- Efficient resource allocation
- Optimized dosage
- Chronic disease management

Organ Simulation for Medical Training

Digital twins of organs, such as the heart or liver, are created to simulate human anatomy and physiology. These models are used for medical training, surgical planning, and research, allowing doctors to practice procedures or test medical devices without risk to real patients.

- Surgical Planning
- Testing medical devices
- Minimized surgical risk
- Medical Education
- Reduced learning curve
- Access to complex cases

Predictive Health Monitoring

By combining data from wearable devices, sensors, and electronic health records, digital twins can continuously monitor a patient's vital signs (e.g., heart rate, blood pressure, glucose levels). These models can predict potential health issues, such as heart attacks, strokes, or diabetes complications, enabling early intervention and proactive care.

- Continuous Monitoring
- Early detection
- Real-time alerts
- Preventive healthcare
- Proactive care

Drug Development and Testing

Digital twins are used in the pharmaceutical industry to simulate the human body's response to new drugs. By modeling individual patients' responses to different treatments, researchers can predict how new drugs will behave, test efficacy, and identify potential side effects before clinical trials, speeding up drug development.

- Personalized drug testing
- Simulate drug response
- Simulate drug efficacy
- Increased cost-effectiveness
- Potential side effect identification
- Simulate long-term effects

Surgical Planning and Simulation

Surgeons can use digital twins to simulate complex surgeries. These models replicate the patient's anatomy and conditions, helping surgeons plan the procedure more accurately, anticipate challenges, and reduce the risk of complications during actual surgery.

- Increased accuracy
- Preoperative visualization
- Surgical challenge identification
- Surgical risk reduction
- Increased time efficiency
- Personalized Surgery

Patient-Specific Prosthetics and Implants

Digital twins of individual patients can be created to design and customize prosthetics or implants that match their unique anatomical features. This results in better-fitting devices that improve functionality, comfort, and overall patient satisfaction.

- Improved comfort
- Enhanced functionality
- Improved surgical planning
- Faster recovery
- Reduced risk of complications
- Increased patient satisfaction

Chronic Disease Management

Digital twins can be used to manage chronic diseases like asthma, diabetes, or cardiovascular conditions. These models integrate continuous data from monitoring devices and predict disease progression, enabling personalized management plans that are adjusted in real-time based on the patient's current condition.

- Progression prediction
- Real-time adjustments to treatment

- Improved medication management
- Reduction in hospitalization
- Long-term health management

Epidemiology and Disease Spread Simulation

Digital twins can be applied in public health to model the spread of infectious diseases. By creating virtual populations with specific health data, these models can simulate disease transmission, predict outbreaks, and help policymakers make data-driven decisions to manage and mitigate public health crises.

- Disease transmission modelling
- Outbreak prediction
- Targeted intervention strategies
- Medical resource allocation
- Preventive measure impact evaluation

Digital twins in life sciences and medical applications are transforming healthcare by creating dynamic virtual replicas of patients, organs, and entire systems, enabling more accurate diagnosis, personalized treatment, and improved operational efficiency. These virtual models integrate data from various sources, including medical history, genetic profiles, diagnostic imaging, and real-time information from wearable devices, providing clinicians with detailed, patient-specific simulations. In personalized medicine, digital twins allow for the simulation of different treatment options, helping doctors to predict how individual patients will respond to various therapies or surgeries.

For instance, using a digital twin of a patient's heart, physicians can plan cardiac procedures with greater precision and tailor interventions to the specific needs of the individual, minimizing risk and improving outcomes.

Beyond individual patient care, digital twins are playing a key role in accelerating drug development and optimizing clinical trials. By creating virtual models of organs or even specific cells, researchers can test how new drugs interact with the body, predict efficacy, and identify potential side effects before clinical trials begin. This approach reduces the reliance on animal testing, speeds up the process of drug discovery, and helps in the design of more targeted therapies. Companies like Insilico Medicine use AI-driven digital twins to simulate how drugs will affect various biological systems, helping identify the most promising drug candidates early in the process.

In the realm of surgery, digital twins are used for pre-surgical planning and simulation, allowing surgeons to rehearse complex procedures virtually before performing them. Technologies like Surgical Theater and Materialize offer 3D models of patient anatomy based on imaging data, such as MRIs or CT scans, enabling surgeons to visualize and practice procedures, reducing errors and enhancing precision. These tools are particularly useful for intricate surgeries, such as neurosurgery or orthopedic procedures, where detailed planning and visualization can significantly improve patient outcomes.

Digital twins also play a critical role in the continuous monitoring and optimization of medical devices.

For example, digital twins of medical devices, like pacemakers or insulin pumps, can be used to monitor real-time performance, detect potential malfunctions, and predict when maintenance or upgrades are needed. By integrating sensor data from these devices, manufacturers and healthcare providers can ensure that equipment is functioning optimally, leading to better patient safety and device longevity. Companies like Medtronic leverage digital twin technology to enhance the performance and reliability of their medical devices.

In addition to individual care, digital twins are being used to optimize healthcare systems at large. Hospitals and clinics are using digital twins to simulate and improve patient flow, resource allocation, and staff scheduling. For example, virtual models of hospital operations allow administrators to predict patient demand, optimize bed utilization, and improve the overall efficiency of healthcare delivery. This approach helps reduce waiting times, streamline processes, and ensure that resources are being used effectively, ultimately improving the quality of care and patient satisfaction.

On a larger scale, digital twins are being applied to public health and epidemiology, where they help track disease trends, simulate disease spread, and predict health outcomes across populations. During the COVID-19 pandemic, digital twin models of the virus's spread were used to inform policies, optimize healthcare resource deployment, and plan interventions, helping public health authorities respond more effectively to the crisis. Similarly, digital twins are used to model the spread of infectious diseases, allowing for better preparedness and targeted public health responses.

Wearable devices, such as smartwatches and fitness trackers, also contribute to the creation of personal digital twins by continuously gathering data on key health metrics like heart rate, sleep patterns, physical activity, and blood sugar levels. This real-time data can be integrated into a digital twin model to provide ongoing insights into a patient’s health, enabling proactive interventions and personalized health recommendations. For example, wearables integrated with digital twin technology can alert both patients and healthcare providers to early signs of health issues, such as a rise in blood pressure or irregular heart rhythms, allowing for timely treatment and prevention.

In oncology, digital twins are proving invaluable by simulating tumor growth and predicting how a specific tumor will respond to various treatments, including chemotherapy, radiation, or immunotherapy. By creating digital models of tumors and their surrounding tissue, clinicians can explore different treatment options, optimize dosages, and reduce side effects. This technology enables personalized cancer care, where treatment plans are specifically tailored to the unique characteristics of a patient's cancer, improving the chances of a successful outcome. Companies like Kheiron Medical Technologies are using digital twins to model breast cancer tumors and predict how they will respond to different interventions.

5.2. Tools Used for Digital Twins in Life Sciences and Medical Applications

5.2.1. Sensors

In the life sciences and medical fields, sensors are used to monitor a patient’s real-time physiological parameters, such as heart rate, blood pressure, glucose levels, oxygen saturation, temperature, and brain activity. Wearable sensors, such as those in fitness trackers or medical devices (e.g., continuous glucose monitors), collect data that is crucial for continuous health monitoring, chronic disease management, and early detection of medical conditions.

5.2.2. IoT Devices

IoT (Internet of Things) devices in healthcare connect medical equipment, wearables, and patient monitoring systems to the Internet, enabling the continuous collection of data. Examples include smart thermometers, ECG monitors, insulin pumps, and pulse oximeters. These devices transmit real-time data to healthcare providers, offering insights into a patient's condition remotely. IoT is especially important in managing chronic conditions and enabling telemedicine, where doctors can remotely monitor patients and adjust treatment plans.

5.2.3. Data Transmission

Data transmission is crucial for transferring the collected sensor and device data from patients to healthcare systems or cloud platforms. This typically involves wireless technologies like Wi-Fi, Bluetooth, 5G, or LoRaWAN. The data is transmitted securely to ensure privacy, enabling real-time monitoring, quick response to changes in patient condition, and integration of health data across systems for decision-making. Data transmission is essential for remote patient monitoring, telemedicine, and the integration of wearable health technology with healthcare providers' IT systems.

5.2.4. Data Storage and Processing

The data collected from sensors and IoT devices is stored and processed in centralized cloud-based platforms or on-premise servers. Cloud computing allows healthcare professionals to access large volumes of patient data from multiple sources in real time. This centralized data storage supports the analysis of health trends, monitoring of chronic conditions, and predictive modeling. Processing this data enables insights into patient health, helping doctors make informed decisions, track patient progress, and develop personalized treatment plans. Cloud-based systems are also scalable, allowing health organizations to manage vast amounts of data efficiently.

5.2.5. Simulation and Modelling

Simulation and modeling tools are used to replicate complex biological systems and human anatomy to better understand diseases, predict health outcomes, and design effective interventions. For example, digital twins of organs or entire patients allow for surgical planning, drug testing, or organ transplantation simulation. These tools help in the development of new medical technologies, personalized medicine, and understanding the progression of diseases. Simulations can also be used to predict the impact of lifestyle changes or medication adjustments on a patient's health.

5.2.6. Machine Learning and Prediction

Machine learning (ML) and predictive analytics are key components in the life sciences and medical fields for analyzing large datasets and making predictions about patient health. ML algorithms are used to identify patterns in medical data (e.g., identifying early signs of diseases like cancer or Alzheimer's), forecast patient outcomes, and assist in clinical decision-making. Predictive models can forecast disease progression, anticipate potential complications, or assess the risk of hospitalization. ML is also applied in drug development, genetic research, and personalized healthcare models by identifying effective treatments based on individual patient data. For example, ML models can predict the likelihood of heart attacks, detect anomalies in imaging scans, and recommend tailored treatment plans.

5.3. Case studies for Life Sciences and Medical Applications

Below is presented several projects regarding Life Science and Medical Application in which Catholic University of Valencia was involved.

- **DART (Diabetes- Augmented Reality Training)**

DART project aims to promote synergies between sport and health, promote inclusion in sports, promote health-enhancing physical activity for people with diabetes type I and II, encourage healthy lifestyles and raise awareness of the added value of sport and physical activity. DART objectives will be achieved through the design and implementation of innovative digital tools and training e-modules. Specifically, the DART project will develop and implement: a) an innovative, fun and eco-friendly Mobile app in 7 language versions using an Augmented reality Personal trainer teaching diabetic patients specialized physical exercises that will help reduce blood pressure, lower the levels of fats in the blood, keep the heart healthy, improve blood sugar levels and prevent excess weight gain. Also, the app will include geofence technology for outdoor activities, a customized calendar for inserting medicines, doctors' appointments, etc. and an insulin dose reminder; b) 30 interactive e-modules based on Moodle targeting Physical Education teachers including a series of Podcasts; c) Awareness raising Events (Multiplier and live streaming) targeting a wider audience of Diabetic patients (type I and II) and their families from all countries involved and above.

- **NONNA (aNalysing cOgnition through Natural laNguage in older Adults)**

NONNA is a research project exploring how spontaneous language use can reveal insights into cognitive abilities in older adults. By analyzing natural language patterns, the project aims to understand cognitive processes related to aging, ultimately leading to better detection and intervention strategies for cognitive decline. Real-world case studies involving elderly individuals to identify cognitive decline through voice interaction. Data collection focuses on speech patterns, response times, and linguistic complexity during interactions with the NONNA voice assistant.

- **BHR VLC (Brain Health and Resilience Valencia Challenge)**

A collaborative research and innovation proposal is underway to establish in Valencia an internationally recognized hub for the study of resilience and brain health. The challenge involves creating a people-centered ecosystem of excellence, co-created and co-developed by participants. Coordinated from UCV (Catholic University of Valencia) and open to participation from universities within the Community, nationwide, and from other countries. This hub aims to bring together businesses, technological and innovation centers, as well as healthcare institutions. Moreover, neuromodulation is a pivotal component of this initiative, leveraging advanced techniques such as Transcranial Magnetic Stimulation (TMS). By integrating neuromodulation into our research framework, we aim to explore the direct modulation of brain activity to enhance resilience and promote brain health.

- **Walkable Cities Instruments**

This project, which increases physical activity in neighborhoods with low walkability levels, presents an important connection with the health of the city's coast, which extends through several interrelated aspects. By actively promoting a more active and healthier lifestyle among residents, we not only address the challenge of improving public health and reducing diseases related to physical inactivity but also generate beneficial indirect impacts on the coastal environment. Promoting physical activity leads to a decrease in motor vehicle use, which in turn reduces air pollution, a critical factor affecting air quality throughout the region, including coastal areas. This reduction in air pollution has positive effects on water quality and marine biodiversity by minimizing the entry of air pollutants into the aquatic environment. Furthermore, by encouraging people's connection with nature through outdoor physical activity, greater environmental awareness and more responsible care of coastal ecosystems are promoted, which contributes to their long-term preservation. In summary, the project not only seeks to improve the health and well-being of residents, but also aims to protect and conserve the natural coastal environment, thus creating a positive and sustainable impact on the health of Valencia's coast

5.4. Comparison of Case Studies

Case Study	DART	NONNA	BHR VLC	Walkable Cities
Sensors	Acelerometers, IMU, GPS, heart rate monitor	Voice sensors (microphones embedded in devices) biometric sensors, heart rate and stress level monitor	Non-invasive sensors, EEG devices, wearable sensors Environmental (e.g., light and noise levels).	-
IoT Devices	Smartwatch, Cellular	Azure-compatible smart speakers or microphones, Azure IoT Hub	Wearable health monitors (e.g., smartwatches, fitness bands) and brain health devices (EEG headbands)	-
Data Transmission	Cellular, Wi-Fi, or any internet conection	Secure data transmission via Azure IoT Hub using MQTT, HTTPS, or AMQP protocols	Wi-Fi, LoRaWAN, cellular networks for cloud-based transmission	Wi-Fi, LoRaWAN, cellular networks for cloud-based transmission
Data Storage and Processing	Cloud storage (UCV forms and Cloud, Azure) for localized databases for infrastructure metadata	Azure Cloud, Azure Cognitive Services, (Speech-to-Text API and Text Analytics AP).	Azure Data Lake, Azure SQL Database	Cloud storage systems (Google)
Simulation and Modelling	-	Natural Language Processing (NLP) models	Brain health trajectory models	-
Machine Learning and Prediction	AI algorithms using predictive models (Python, MATLAB)	Azure machine learning	AI algorithms using predictive models (Python, MATLAB)	Linear and logistic regressions (SPSS) to predict physical activity (Python, MATLAB)

Tabel 3. Illustrates the tools and methods used in DART, NONNA, BHR VLC and Walkable Cities

6. Comparison of Tools between Built Environment, Agriculture and Life Sciences and Medical Applications

Tool	***Built Environment***	***Agriculture***	***Life Sciences and Medical Applications***
Sensors	Temperature, Occupancy, Humidity, Air Quality, Lighting, Pressure, Accelerometer	Temperature, Humidity, pH Soil Moisture, Light, Camera, GPS tracker, LiDAR	Optical, Piezoelectric, Temperature, Heart Rate, Accelerometer, GPS
IoT devices	Smart Meters for; Energy, Electricity, Gas, HVAC, Lighting	Weather Station, Drones, Multispectral and Hyperspectral Cameras	Smartwatch, Fitness Tracker, Smart Inhalers, Neurostimulators
Data Transmission	Cellular, Wi-Fi, LoRaWAN for low-power	Cellular, Wi-Fi, LoRaWAN for low-power	Cellular, Wi-Fi, or any internet conection
Data Storage and Processing	Cloud storage (AWS, Azure, Siemens MindSphere, Hottinger Baldwin Messtechnik)	Cloud Storage (Microsoft Cloud, Azure) for localized databases for infrastructure metadata	Cloud storage (Microsoft Cloud, Azure) for localized databases for infrastructure metadata
Simulation and Modelling			
Machine Learning and Prediction	AI algorithms for predictive maintenance, Energy Efficiency, and Predictive Consumption Models (Python, MATLAB)	AI algorithms for evaluation of climate data or soil conditions, prediction of growth and	AI algorithms for predictive physical activity, more efficient exercises, and creating predictive models (Python, MATLAB)

Table 4. Comparison between sectors of Built Environment, Agriculture, Life Sciences and Medical Applications

The tools used in built environments, agriculture, and life sciences/medical applications all serve to enhance efficiency, optimize operations, and improve decision-making, but their specific technologies and applications differ due to the nature of each sector. In the built environment, sensors such as motion detectors, temperature, humidity, and air quality sensors are commonly used in smart buildings to monitor and control environmental conditions, while IoT devices help integrate these systems for real-time management. Data transmission tools like Wi-Fi, Zigbee, and LoRaWAN are widely used to connect IoT devices to centralized systems, and data storage is typically handled by cloud services, providing scalability and ease of access. In agriculture, sensors for soil moisture, temperature, light, and pH are used to monitor crops and optimize irrigation and fertilization. IoT devices in agriculture, such as GPS-guided tractors and drones, help collect large datasets that are transmitted via cellular or low-power wide-area networks (LPWAN). Data storage tools include both cloud and edge computing solutions for real-time analysis. AI and machine learning are applied for predictive analytics, crop yield forecasting, and pest detection. In life sciences and medical applications, sensors like ECG monitors, glucose sensors, and wearable health devices continuously collect health data from patients. IoT devices, including smart pacemakers and wearable fitness trackers, feed data to cloud-based platforms for integration and analysis. Data transmission tools in healthcare, like Bluetooth and 5G, ensure that real-time health data is transmitted securely. Data storage in the medical field involves robust, HIPAA-compliant systems, with both cloud storage and local medical records systems. AI and machine learning tools are heavily utilized for diagnostic purposes, predictive health analytics, and personalized treatment plans, helping to provide deeper insights and improve patient outcomes. Across all sectors, the synergy of sensors, IoT, data transmission, storage, and AI/ML tools is transforming how data is collected, processed, and used to drive decision-making and optimization.

7. Models Used in Digital Twins

In the context of Digital Twins, a Model refers to a digital representation or simulation of a physical object, system, or process. This model is created using data, algorithms, and various technologies to reflect the real-world counterpart as accurately as possible. Digital twins are used to simulate, monitor, and optimize physical assets, systems, or environments in real time. There are several types of models that are present in the creation of digital twins depending on the target area. The key roles of the models include simulation and testing, monitoring and diagnostics, optimization and prediction. For the built environment, agriculture and Life Sciences & Medical Applications the most common modeling technique used is Data-Driven/Predictive.

7.1. Data-Driven/Predictive

A data-driven model in the context of digital twins refers to a model that leverages large volumes of real-time and historical data to simulate, analyze, and predict the behavior of physical assets or systems. Unlike traditional models that are based on predefined rules or physical principles (such as the physical model or behavioral model), data-driven models rely on data patterns, trends, and correlations extracted from sensors, monitoring systems, and other data sources to make predictions or inform decisions.

A predictive model in the context of digital twins is a type of model that uses data-driven techniques (such as machine learning, statistical analysis, or other advanced analytics) to forecast future events or behaviors based on historical data, real-time inputs, and simulation results. It is designed to anticipate how a physical system or asset will behave in the future, allowing for better decision-making, proactive management, and optimized operations.

In a digital twin framework, a data-driven model continuously receives and processes data from the physical asset or environment, and then uses this data to generate insights, identify trends, detect anomalies, or optimize performance. These models can learn and improve over time as they are fed more data, enabling more accurate forecasting and decision-making. A predictive data-driven model continuously integrates data from tools such as sensors, IoT devices, and other sources to simulate and predict the future performance or condition of the physical asset. This model can predict maintenance needs, energy consumption, equipment failures, or system performance under varying conditions.

7.2. Gradient Boosting: A Mathematical Deep Dive

One of the most important techniques used by forecasting models is gradient boosting. This method has been extensively applied in areas like regression, classification, and time-series forecasting due to its robustness and flexibility (Friedman, 2001). This technique is used extensively in models like Skforecast, XGBoost, LightGBM and CatBoost.

In this section, we delve into the underline mathematics of the gradient boosting model, focusing on its theoretical framework, optimization process, and how it applies to real-world datasets, such as predicting electricity consumption.

7.3. Problem Formulation

The primary task is to be able to predict a quantity of interest, for instance, electricity consumption denoted by y based on a set of input features $\boldsymbol{x} = [x_1, x_2, \dots \dots, x_n]$, where x_i is a vector defined by $x_i = \left[x_i^{t_1}, x_i^{t_2}, \dots, x_i^{t_k}\right]^T$. Here $x_i^{t_j}$ is the reading of feature x_i at time t_j, representing potentially relevant influencing factors, such as:

- x_1: Past electricity usage data.
- x_2: Past humidity data.
- x_3: Past internal temperature.

Thus, the feature matrix can be represented as:

$$\boldsymbol{x} = \begin{bmatrix} x_1^{t_1} & \cdots & x_n^{t_1} \\ \vdots & \ddots & \vdots \\ x_1^{t_k} & \cdots & x_n^{t_k} \end{bmatrix},$$

where n is the number of different factors. Given this dataset $\boldsymbol{x}$, our goal is to build a model $F(\boldsymbol{x})$ that minimizes the expected value of a loss function $L(y, F(\boldsymbol{x}))$, expressed as:

$$F^*(\boldsymbol{x}) = arg \min_F E[L(y, F(\boldsymbol{x}))],$$

where the expectation $E[\cdot]$ captures the overall error across the dataset (Hastie *et al.*, 2009).

For regression problems, common choices for L include:

1. **Squared Error Loss**:

$$L(y, F) = \frac{1}{2}(y - F)^2,$$

commonly used in basic regression tasks.

2. **Absolute Error Loss**:

$$L(y, F) = |y - F|,$$

providing robustness to outliers but less smooth for optimization (James *et al.*, 2013).

3. **Huber Loss** (a robust alternative):

$$L(y,F) = \begin{cases} \frac{1}{2}(y-F)^2, & if \quad |y-F| \leq \delta \\ \delta\left(|y-F| - \frac{\delta}{2}\right), & if \quad |y-F| > \delta \end{cases}.$$

This function is a combination of the Mean Squared Error (MSE) and Mean Absolute Error (MAE), behaving like MSE for small residuals and MAE for large residuals, (Huber, 1964). In the formula δ is a threshold parameter that determines the switch between MSE and MAE behavior. The parameter δ needs to be tuned depending on the dataset.

7.4. Stagewise Additive Modelling

Gradient boosting builds the model $F(\boldsymbol{x})$ iteratively as a sum of simpler models (weak learners). At the mth iteration:

$$F_m(\boldsymbol{x}) = F_{m-1}(\boldsymbol{x}) + \nu\, h_m(\boldsymbol{x})$$

where:

- $F_{m-1}(\boldsymbol{x})$: The model after m−1 iterations.
- $h_m(\boldsymbol{x})$: The weak learner at step m, often a decision tree.
- ν: Learning rate ($0 < \nu \leq 1$) controlling the contribution of $h_m(\boldsymbol{x})$.

If the initial model is denoted by $F_0(\boldsymbol{x})$ then the above equation can be written as:

$$F_m(\boldsymbol{x}) = F_0(\boldsymbol{x}) + \sum_{j=1}^{m} \nu\, h_j(\boldsymbol{x})$$

7.4.1. Weak Learner

The term *weak learner*, denoted by $h_m(\boldsymbol{x})$, refers to a simple model that performs slightly better than random guessing on the task at hand. In gradient boosting, weak learners are used as building blocks, and their predictions are combined iteratively to form a strong, highly accurate model, (Friedman, 2001).

The most common weak learners in gradient boosting are decision trees, specifically shallow trees (trees with limited depth, such as 1–5 levels). These shallow trees are also called stumps when the depth is just 1. Shallow trees are chosen because they are computationally efficient and reduce the risk of overfitting in each boosting step, (Breiman, 1996).

Each weak learner is trained to approximate the residuals (errors) of the current model at that iteration. For instance, if the current model predicts $F_{m-1}(\boldsymbol{x})$ and the true value is y, the weak learner is trained to minimize the error:

$$r_i = y_i - F_{m-1}(\boldsymbol{x}_i)$$

This incremental approach ensures that each weak learner contributes to correcting the mistakes of the previous model, (Friedman, 2001).

The use of Decision Trees is usually the common choice for weak learners as they are interpretable and handle non-linear relationships well, (Breiman, 1996). In addition, they do not require extensive preprocessing of data (e.g., feature scaling or normalization), (Quinlan, 1986).

On their own, weak learners are not powerful enough to model complex patterns. However, gradient boosting leverages many of them sequentially to build a strong model.

7.4.2. Learning Rate ν

The learning rate is a crucial hyperparameter in gradient boosting that controls the contribution of each weak learner to the overall model. The learning rate, denoted by ν, is a scaling factor applied to the predictions of each weak learner. The updated model at step m becomes:

$$F_m(\boldsymbol{x}) = F_{m-1}(\boldsymbol{x}) + \nu\, h_m(\boldsymbol{x}),$$

where $h_m(\boldsymbol{x})$ is the weak learner's prediction.

A low learning rate reduces the impact of each weak learner, requiring more iterations for convergence. It also encourages finer adjustments, leading to better generalization but increased computation, (Hastie *et al.*, 2009). On the other hand, a high learning rate increases the impact of each weak learner, potentially allowing faster convergence. However, it risks overfitting, as the model may overreact to individual weak learners' errors, (Friedman, 2001).

In practice, learning rates like $\nu = 0.1$ or $\nu = 0.01$ are commonly used. The optimal choice depends on the dataset and the complexity of the problem, (Friedman, 2001).

7.4.3. Loss Function and Negative Gradient

The key idea of gradient boosting is to optimize the loss function $L(y, F)$ by adding weak learners, $h_m(\boldsymbol{x})$, that fit the negative gradient of the loss function at $F_m(\boldsymbol{x})$, (Friedman, 2001). This is the key step in the gradient boosting algorithm.

To begin with, the residuals (errors) are defined mathematically as:

$$r_{im} = -\left[\frac{\partial L(y_i, F)}{\partial F}\right]_{F=F_{m-1}(\boldsymbol{x}_i)}.$$

Here r_{im} represents the residuals, which act as pseudo-responses that will guide the weak learner $h_m(\boldsymbol{x})$, (Breiman, 1996).

7.4.3.1. Squared Error Loss

As mentioned earlier, a common choice of loss function for regression problems is squared error loss, which is given by:

$$L(y, F) = \frac{1}{2}(y - F)^2.$$

The gradient of the squared error loss with respect to the model output F is:

$$\frac{\partial L}{\partial F} = F - y$$

Thus, the residuals become:

$$r_{im} = y_i - F_{m-1}(\boldsymbol{x}_i),$$

which represents the error between the true value y_i and the current prediction $F_{m-1}(\boldsymbol{x}_i)$. At each iteration, the weak learner $h_m(\boldsymbol{x})$ is trained to fit these residuals (Friedman, 2001).

7.4.3.2. Absolute Error Loss

Another option for the loss function is absolute error loss, which is defined as:

$$L(y, F) = |y - F|.$$

The gradient of the absolute error loss with respect to the model output F is:

$$\frac{\partial L}{\partial F} = sign(F - y),$$

where $sign(F - y)$ is the sign function, which returns 1 if $F - y > 0$, and -1 if $F - y < 0$.

Thus, the residuals become:

$$r_{im} = -sign(F_{m-1}(\boldsymbol{x_i}) - y_i)$$

These residuals will guide the weak learner in the subsequent iteration, helping the model focus on the areas with the most error, (James *et al.*, 2013).

7.4.3.3. Weak Learners and Tree Structure

In gradient boosting, weak learners are typically decision trees, (Quinlan, 1986). Each tree partitions the feature space $\mathbb{R}^n$ into J regions $\{R_j^m\}_{j=1}^J$. For a sample $\boldsymbol{x}$, the prediction from the tree at iteration m is given by:

$$h_m(\boldsymbol{x}) = \sum_{j=1}^{J} \gamma_j^m \, 1_{\{x \in R_j^m\}}$$

where:

- $1_{\{x \in R_j^m\}}$ is an indicator function that equals 1 if x belongs to region R_j^m, and 0 otherwise.
- γ_j^m is the value predicted for region R_j^m.

To find γ_j^m, we minimize the loss over all samples in region R_j^m. This involves solving the following optimization problem:

$$\gamma_j^m = arg \min_{\gamma} \sum_{\boldsymbol{x_\iota} \in R_j^m} L(y_i, F_{m-1}(\boldsymbol{x_\iota}) + \gamma)$$

For the squared error loss, the optimal γ_j^m is the mean of the residuals in the region R_j^m:

$$\gamma_j^m = \frac{\sum_{x_\iota \in R_j^m} (y_i - F_{m-1}(x_\iota))}{\sum_{x_\iota \in R_j^m} 1}.$$

This ensures that each weak learner (decision tree) fits the residuals in each region of the feature space optimally (Friedman, 2001).

For the absolute error loss, the optimal γ_j^m is the median of the residuals in the region R_j^m, not the mean as in the squared error case. This is because the median minimizes the sum of absolute deviations.

Formally:

$$\gamma_j^m = Median\left(y_i - F_{m-1}(\boldsymbol{x_\iota})\right), \quad \forall \ \boldsymbol{x_\iota} \in R_j^m.$$

For absolute error loss, the optimization objective is non-differentiable at the residual zero-crossings, but the minimum occurs at the point where the sum of positive deviations equals the sum of negative deviations. This balancing point is precisely the median of the residuals, (Hastie, 2009).

7.4.4. Final Model

After M iterations, the final model is expressed by:

$$F_M(\boldsymbol{x}) = F_0(\boldsymbol{x}) + \sum_{m=1}^{M} \nu\, h_m(\boldsymbol{x})$$

This model combines predictions from all weak learners.

7.4.5. Algorithm Outline

For clarity, here's the full algorithm for gradient boosting:

1. **Initialize:** Set $F_0(\boldsymbol{x}) = arg\,\min_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma)$
2. **Iterate** for m=1,…,M*:*
   - Compute residuals:
   $$r_{im} = -\left[\frac{\partial L(y_i, F)}{\partial F}\right]_{F=F_{m-1}(\boldsymbol{x}_i)}$$
   - Fit a weak learner $h_m(\boldsymbol{x})$ to the residuals r_{im}.
   - Optimize the weak learner's predictions γ_j^m.
   - Update the model:
   $$F_m(\boldsymbol{x}) = F_{m-1}(\boldsymbol{x}) + \nu\, h_m(\boldsymbol{x}),$$
3. **Final Model**

   After *M* iterations the final model is:
   $$F_M(\boldsymbol{x}) = F_0(\boldsymbol{x}) + \sum_{m=1}^{M} \nu\, h_m(\boldsymbol{x})$$

7.4.6. Practical Application to Electricity Prediction

Dataset

- Influencing factors: $\boldsymbol{x_i} = [\text{past electricity usage, humidity, temperature, etc.}]$
- Target: $y_i = electricity\ consumption$

Model Training

1. **Initialization**: Start with a constant model:

$$F_0(\boldsymbol{x}) = arg\,\min_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma) = arg\,\min_{\gamma} \sum_{i=1}^{n} (y_i - \gamma)^2 = \frac{1}{n} \sum_{i=1}^{n} y_i$$

2. **Iteration**: At each step, compute residuals r_{im} and fit a decision tree $h_m(\boldsymbol{x})$. For example, if $y_i = 52$ and $F_{m-1}(\boldsymbol{x_i}) = 44$, the residual is $r_{im} = 8$.

3. **Prediction**: After training M iterations, the model predicts:

$$F_M(\boldsymbol{x}) = F_0(\boldsymbol{x}) + \sum_{m=1}^{M} \nu\, h_m(\boldsymbol{x})$$

8. Examples of Digital Twin models under development at the widening EU-CONEXUS partners with replicability potential towards the associated partners

Between widening partners were identified two projects regarding Digital Twin, NetZeRoCities, in which Technical University of Civil Engineering of Bucharest is involved and SmartLivingEPC project, Frederik University being part of the research.

8.1. NetZeRoCities

NetZeRoCities project identifies several tools and technologies related to digital twin development, particularly in the context of the EFdeN building. The following tools can be transferred and replicated for digital twin technologies:

1. **IES VE (Integrated Environmental Solutions Virtual Environment)**: This simulation platform is used to analyse and optimize the energy performance of buildings. It allows users to create a 3D digital model of a building and assess its performance under various conditions. The software integrates multiple modules for energy use calculation, cost analysis, and life cycle analysis.

2. **IES iScan**: This intelligent solution manages building data to reduce consumption and carbon emissions. It centralizes data from various sources, including Building Management Systems (BMS), utility meters, and sensors, facilitating the analysis and interpretation of energy consumption and indoor comfort data. iScan also enables the creation of Digital Twins for simulating future scenarios and assessing retrofit options.

3. **Machine Learning Models**: The document discusses the integration of machine learning algorithms for monitoring, functionality optimization, simulation, diagnosis, and predictive maintenance. Specific models mentioned include Isolation Forest for anomaly detection and Deep Q-Learning for optimizing HVAC system control.

4. **Data Visualization and Analysis Tools**: The iSCAN platform provides capabilities for visualizing data, creating perspectives for analysis, and generating insights from the analysed data. It allows for the import of measured data and the application of machine learning models to assess building energy performance

These tools collectively support the creation, management, and optimization of digital twins, making them suitable for replication in other projects focused on energy efficiency and sustainability in buildings.

The model identified refers to the Digital Twin created for the EFdeN building project. This Digital Twin serves as a virtual representation of the physical building, allowing for the simulation and analysis of its behaviour, performance, and interactions with various environmental factors. The model integrates real-time data collected from sensors installed throughout the building, enabling continuous monitoring and optimization of its operations.

8.2. SmartLivingEPC

In the context of the SmartLivingEPC project, the model identified refers to the digital twin application that simulates the energy usage, environmental impact, and operational efficiency of buildings, particularly in coastal zones. This model is designed to improve sustainability practices and reduce carbon footprints by considering the unique microclimate and environmental conditions of coastal areas, such as high humidity and varying temperature gradients.

The tools for digital twin technologies identified in the "SmartLivingEPC Project Overview" document include:

1. **Building Information Modeling (BIM) Software**: This software is essential for comprehensive architectural and engineering design, serving as a foundational tool for creating detailed virtual models of buildings.
2. **Digital Twin Platforms**: These platforms enable real-time building performance simulation, allowing for the dynamic representation of the physical systems.
3. **IoT Devices**: These devices are crucial for granular data collection, capturing a wide range of environmental and operational parameters necessary for the digital twin's functionality.
4. **Smart Sensors**: Capable of monitoring various conditions, smart sensors provide the data needed to inform the digital twin's operations and performance assessments.
5. **Data Analytics and Visualization Software**: This software is necessary for interpreting complex datasets generated by the digital twin, facilitating informed decision-making.
6. **Machine Learning Algorithms**: These algorithms are utilized for predictive analytics and optimization of energy consumption, enhancing the digital twin's capabilities.
7. **Integration Platforms**: These platforms facilitate seamless communication between BIM, digital twins, IoT data streams, and smart sensors, ensuring cohesive operation.
8. **Big Data Management Solutions**: These solutions are essential for handling the volume, velocity, and variety of data generated by the digital twin technologies.

These tools can be transferred and replicated in other projects aiming to implement digital twin technologies, particularly in the context of building sustainability and energy performance analysis.

9. Selection of Digital Twin models identified at non-widening EU-CONEXUS partners with replicability potential towards the widening partners

Non-widening universities shared their initiatives toward Digital Twin models, many of which are still in the incipient phase. Each project aims to create a comprehensive digital representation that integrates real-time data, simulations, and predictive analytics to inform decision-making and promote sustainable practices

9.1. Urban & Coastal Lab La Rochelle

The **Urban & Coastal Lab La Rochelle** (UCLR) project, in which La Rochelle University is part of, is developing an open-source web platform that is based on interoperability standards, which serves as a tool for digital twin technologies. The specific tools identified in the document that can be transferred and replicated include:

1. **Open-source Web Platform**: This platform will facilitate the sharing, preservation, citation, and exploration of research data, models, and digital tools.
2. **Catalog Service**: This service will allow users to share and manage research data and models effectively.
3. **TERREZE Data Platform**: An upgraded version of this platform will provide analytics services on-demand, enabling the processing and interpretation of coastal data for various scientific, research, and application purposes.

These tools are designed to support the collection and management of data, which is crucial for the effective implementation of digital twin technologies, particularly in the context of sustainable management of coastal territories as outlined in the project. The emphasis on interoperability and open-source development also suggests that these tools can be adapted for use in other contexts beyond the UCLR project, making them replicable and transferable.

The status of the UCLR project, indicates that it is currently in the development phase. The project is focused on establishing a platform for collecting and formatting data and models, which is part of a broader initiative to create a common data management policy within La Rochelle University. In the short term, the emphasis is on developing the platform and pooling data around various case studies to demonstrate its utility.

Additionally, there are plans for a longer-term development that includes the creation of scientific tools for analysis, simulation, and integration of data and models, with a specific focus on incorporating digital twins.

In the context of the UCLR project, the model identified pertains to the establishment of a platform dedicated to pooling, exploiting, and valorising data, models, and digital tools from various research laboratories at La Rochelle University. The project emphasizes the development of scientific tools that will analyse, simulate, and integrate data and models, particularly focusing on the incorporation of digital twins.

9.2. smartSE

In the context of the smartSE initiative, project that Soth East Technological University was part of, the model associated with digital twins relies on creating a smart city experimental facility. The smartSE facility aims to serve as a living lab that leverages high-quality, reliable data to simulate and optimize urban systems and processes. The specific tools identified in the document that can be transferred and replicated include:

1. **Data Analytic Services**: This offering includes advanced technology and analytical platforms that can be utilized to process real-time data and support the creation and management of digital twins.
2. **Smart City Experimental Sandbox**: This environment allows for testing concepts using regional data, which can be instrumental in simulating and optimizing the physical systems represented by digital twins.
3. **Innovation Imaginarium**: This design-led program fosters startup creation, which may involve the development of new tools and technologies applicable to digital twin applications.
4. **Data Platform**: This platform facilitates data trading and sharing, which is essential for the effective functioning of digital twins, as they rely on accurate and timely data from various sources.

These components from the smartSE initiative can be transferred and replicated to support the development of digital twin technologies in other contexts, particularly in smart city applications. The focus on data, innovation, and collaboration within the project enhances the potential for creating effective digital twin solutions.

SmartSE highlights several key aspects that relate to the concept of a model in digital twins:

1. **Data-Driven Approach**: The smartSE initiative focuses on utilizing data to inform decision-making and enhance public service, which is essential for creating accurate digital representations of physical systems.
2. **Collaboration and Co-Creation**: The project emphasizes co-creation across various stakeholders, including local government, private enterprises, and citizens. This collaborative approach is vital for developing comprehensive models that accurately reflect the complexities of urban systems.
3. **Focus on Sustainability**: The smartSE initiative aims to address sustainability challenges through data-driven insights, which suggests that the models developed will incorporate environmental factors and performance metrics relevant to sustainability goals.
4. **Experimental Laboratories**: The facility offers experimental laboratories where new processes, products, and business ideas can be tested. This aspect indicates that mathematical models will likely be employed to simulate the behaviour of these innovations in a controlled environment.

9.3. Cúpla Trá

Cúpla Trá, project that Soth East Technological University was part of, employs digital twin technology for environmental analysis in a coastal region of County Waterford, Ireland. several functionalities and methodologies that can be considered as tools or components of the digital twin framework are identified:

1. **Digital Twin Platform**: The project aims to develop and implement a digital twin platform that maps the current and natural environment of the area. This platform will integrate various datasets, which suggests the use of software tools for data integration and visualization.
2. **Data Integration Tools**: The project will incorporate existing environmental datasets and socio-economic data from various sources, indicating the need for tools that can aggregate and harmonize data from different governing bodies and organizations.
3. **Predictive Analysis Tools**: The document mentions the ability to conduct predictive analysis of the inter-dependent factors affecting the environment. This implies the use of analytical tools capable of modeling and simulating different scenarios based on the integrated data.
4. **Interactive "Mission Room"**: The project includes an immersive, interactive space for stakeholder awareness and participation, which suggests the use of visualization and simulation tools that allow users to interact with the digital twin in a meaningful way.
5. **Monitoring Tools**: The document references the importance of monitoring greenhouse gases and river health, indicating the need for real-time data processing and monitoring tools that can track environmental changes and impacts.

In the context of the "Cúpla Trá" project, the model identified refers to the digital twin platform that aims to create a comprehensive and holistic representation of the coastal region in County Waterford, Ireland. This model is designed to simulate and analyze both human and non-human behavioral patterns and interactions within the environment.

9.4. Evolve-Evalue

UCV Evolve-Evalue aims to combine two digital twins for medical training. It utilizes the CAE Maestro Evolve platform for interactive simulations with virtual patients and an evaluation tool for assessing student performance. The goal is to enhance medical education and training through realistic simulations and assessments.

The tools for digital twin technologies identified in the project include:

1. **CAE Maestro Evolve Software**: This software serves as an interactive virtual learning platform that facilitates medical training and content development. It allows for the creation of virtual patients and medical equipment, as well as the implementation of various teaching tools and pre-programmed Simulated Clinical Experiences (SCEs). However, it is noted that the current access is in demonstration mode, which limits its use.
2. **UCV Evalua Application**: This application is developed specifically for the university and includes a pool of approximately 500 questions for evaluating student performance. It allows teachers to organize pre- and post-simulation exams, customizing the number and difficulty of questions based on an extensive question pool.

These tools can be transferred and replicated in other contexts by adapting the software and application functionalities to meet the specific needs of different educational or training environments, particularly in medical training. The integration of these tools can enhance the simulation and evaluation processes in various settings.

The model identified pertains to the digital twin for medical simulation training. Specifically, it involves the CAE Maestro Evolve platform, which serves as an interactive virtual learning environment. This model allows for the creation of virtual patients, where various pathologies and physiological responses can be assigned and altered based on student interactions.

Despite the promising benefits, the projects also highlight common challenges, such as the complexity of data integration, the need for robust infrastructure, and the importance of stakeholder collaboration. Collectively, these initiatives underscore the necessity of interdisciplinary approaches and innovative solutions to address the multifaceted challenges faced by coastal and urban areas, ultimately aiming for improved decision-making and sustainable development.

10. Conclusion

For Digital Twins, tools used regarding sectors of built environment, agriculture, life sciences, and medical applications are generally of the same six types. Sensors, IoT devices, Data transmission, Data storage and processing, Simulation and modelling, Machine Learning and Prediction. The main difference between the sectors are the usage of specific sensors and IoT devices depending on the desired type of information that is to be collected (building parameters, soil data, biological signals). When it comes to data transmission and storage, all sectors use a mix between cellular, Wi-Fi and LoRaWAN for transmission and cloud-based platforms for storage and processing purposes. Cloud-based platforms are popular in digital twin applications in all sectors due to their scalability, real-time data access, and ability to integrate various systems and stakeholders. These platforms can efficiently handle large volumes of data generated by sensors and IoT devices, storing, processing, and analyzing it in a centralized location. Usage of Python and MATLAB is seen to be very common in Machine Learning and Prediction for all sectors. The focus of machine learning and prediction in digital twin applications is centered on specific areas for different industries. In the built environment, it is primarily aimed at predictive maintenance, optimizing asset lifespan and reducing downtime. For agriculture, the focus is on growth prediction and soil concentration to enhance crop yields and monitor soil health. In life sciences and medical applications, machine learning is used to predict physical activity and monitor biological parameters, enabling personalized healthcare and early detection of medical conditions.

For interdisciplinary research, PhD candidates can be encouraged to pursue interdisciplinary research that spans across the built environment, agriculture, life sciences, and medical applications. For instance, a PhD candidate could work on developing advanced machine learning algorithms for predictive maintenance in the built environment, while also exploring their applications in healthcare for predictive physical activity or biological parameter monitoring. Cotutelle programs can be structured to encourage candidates to work at the intersection of multiple sectors. For example, a joint program between universities in engineering and life sciences could allow students to develop and apply IoT and sensor technologies for both smart buildings and health diagnostics, fostering cross-disciplinary expertise.

Regarding sensors and IoT devices, PhD candidates could work on the development and optimization of sensors and IoT devices, with a focus on their specific applications in various sectors. For example, a student might research sensor innovations for agriculture (e.g., for soil concentration and growth prediction) or medical devices that track biological signals.

Cotutelle programs could encourage research on sensor technologies that can be applied universally across sectors but tailored to the needs of each (e.g., sensors for environmental monitoring in agriculture and built environments or wearable health-monitoring devices).

When predictive technologies and innovation is considered, growth prediction, and biological parameter monitoring are central themes in all sectors, PhD candidates could develop innovative predictive technologies using machine learning, IoT, and simulation models to improve accuracy and functionality. For example, a focus on predictive analytics to anticipate equipment failure in the built environment or predictive health monitoring in medical applications could significantly advance these fields. Students in cotutelle programs can focus on predictive technologies that can be adapted across sectors, fostering innovation that could lead to global breakthroughs in healthcare, agriculture, and infrastructure management.

11. Tables

12. Figures

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