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Optimizing Facilities Management Through Artificial Intelligence and Digital Twin Technology in Mega-Facilities

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Abstract: Mega-facility management has long been inefficient due to manual, reactive approaches. Current facility management systems face challenges such as fragmented data integration, limited predictive systems, use of traditional methods, and lack of knowledge of new technologies, such as Building Information Modeling and Artificial Intelligence. This study examines the transformative integration of Artificial Intelligence and Digital Twin technologies into Building Information Modeling (BIM) frameworks using IoT sensors for real-time data collection and predictive analytics. Unlike previous research, this study uses case studies and simulation models for dynamic data integration and scenario-based analyses. Key findings show a significant reduction in maintenance costs (25%) and energy consumption (20%), as well as increased asset utilization and operational efficiency. With an F1-score of more than 90%, the system shows excellent predictive accuracy for equipment failures and energy forecasting. Practical applications in hospitals and airports demonstrate the developed ability of the platform to integrate the Internet of Things and Building Information Modeling technologies, shifting facilities management from being reactive to proactive. This paper presents a demo platform that integrates BIM with Digital Twins to improve the predictive maintenance of HVAC systems, equipment, security systems, etc., by recording data from different assets, which helps streamline asset management, enhance energy efficiency, and support decision-making for the buildings' critical systems.

Keywords: facility management (FM); Building Information Modeling (BIM); internet of things (IoT); digital twin (DT); digital trio; employer information requirement (EIR); artificial intelligence (AI)

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1. Introduction

Megaprojects, including airports and smart cities, face many challenges during the operation period [1], with data showing that 30% of facility management budgets are wasted due to unplanned maintenance and inefficient resource allocation. Current FM approaches remain limited due to huge documents, unorganized RFI correspondence, delays in getting information at the right time, and inefficient resource utilization. These reasons in megaprojects cause many difficulties in applying DT and digital operations for any facility.

The appearance of new technologies, such as Building Information Modeling (BIM) and Artificial Intelligence (AI), encourages stakeholders to control, calculate, and predict the maintenance cost for any building; the establishment of large-scale projects, whether between institutions or countries, has especially had a great impact on both economic and promotion uses. Hence, inefficiencies in large-scale construction projects can be solved by integrating AI and DT into facility management (FM).

Although some research has explored the integration of AI, DT, and BIM, huge shortcomings remain in the practical application for these frameworks. Previous studies have not addressed interoperability challenges, scale concerns, or huge data that should be organized and controlled through a cloud system or a custom platform. Furthermore, approaches that incorporate AI and DT lack adaptability to diverse systems and real-time responsiveness and leave critical gaps in predictive maintenance and lifecycle management [2].

This paper highlights the importance of high-class BIM models being prepared while also observing the Employer's Information Requirements (EIRs) and the Asset Information Requirements (AIRs). It also emphasizes that LOD 500 parameters play an important role for linking BIM models with real-time data retrieved from Internet of Things (IoT) sensors. Rather than the traditional one-sided approach found in many studies surrounding DT, this paper delves into the importance of defined parameters and guides you through categorizing and outlining the hypothesis for parameter selection to facilitate the function of the DT platform. This strategy emphasizes that the power of DT systems for higher predictive maintenance, energy optimization, and real-time decision-making is not entirely exploited without accurate parameterization [3].

The integration of AI-powered frameworks helps facilities managers move from reactive to proactive management by improving data-driven decision-making and predictive maintenance capabilities [3]. Meanwhile, DT technology improves operations and system monitoring by creating dynamic, real-time replicas of physical facilities [4]. When combined with IoT and BIM, these two AI-powered DT frameworks improve resource utilization and reduce maintenance costs, while many existing implementations neglect the challenges associated with megaprojects, such as interoperability, cybersecurity, and user-friendliness.

This study proposes a novel AI-Powered DR platform for megaprojects, first by addressing the current gaps in the literature review section, and second by overcoming challenges in FM and operations. The case study presents a platform to integrate real-time IoT sensors data with BIM models to be developed to store data to build predictive maintenance capabilities for systems such as heating, ventilation, and air conditioning (HVAC), fire, temperature control, closed circuit television (CCTV), and humidity.

The integration of BIM, IoT, and AI goes beyond conventional frameworks by creating scenario analyses, BIM models with FM parameters, and sensor readings able to monitor and create predictive maintenance [3].

A previous research proposed a closed-loop interactive Digital Twin (DT) framework in which Building Information Modeling (BIM) is included for implementation in human–robot collaborative construction workflows (2023). To illustrate, AI-powered robotics were shown to operate alongside BIM models, working with the purpose of improving construction process efficiency and precision. At the same time, the work completed in this research, which consists of creating a Digital Twin with the purpose of predictive maintenance, is something not previously implemented or studied [4].

The objective of this paper is to investigate the advantages of AI and DT tools in the management of large-scale construction project facilities, including predictive maintenance, security controls, and safety, which will help with the reduction of maintenance costs and give full control for the operator to avoid any sudden failure for any facility. This paper explores a proposal for a platform that can collect real-time data, which helps decision-making processes and provides scenario simulations to identify best practices and potential challenges, offering guidelines for the future implementation of such services in large scale facilities. This paper is a guide for any organization that is willing to improve the efficiency and sustainability of mega-facility management in any building by discussing the challenges and putting a road map for applying DT with AI algorithms to prepare an easy-use predictive platform.

2. Literature Review

The combination of AI and DT technology in FM is receiving considerable focus for its ability to enhance operational efficiency and decision-making in challenging environments like large scale facilities through data-driven insights and predictive analysis, while DT technology creates real-time follow-up and enables better monitoring and operation optimization. This integration has gained attention for its potential to address critical challenges compared to existing studies, in which many did not address key challenges, such as interoperability, scalability, real-time analysis and security. This research identifies these gaps and demonstrates how the proposed AI-powered DT platform bridges them and offers a comprehensive solution for the operation process [5].

To build a DT platform for megaprojects such as hospitals and airports requires three components. First, a good structured BIM model with parameters for each facility. Second, using the IoT and AI in collecting and controlling data. Third, good visualization, with an easy-to-use platform and IoT DT technology, which enhances FM by providing advanced visualization. Remote FM was achieved with augmented reality (AR) and virtual reality (VR) integrated in the DT models, which were used as well for classification concepts, relating them through the literature review process at hand [6].

2.1. BIM Technology in Facility Management

BIM is a digital representation of the physical and functional characteristics of a building that serves as a shared knowledge resource for information about its design, construction, and operation [7]. When applied to facilities management, BIM models function as thorough databases for spatial layout, asset descriptions, and building system information that underlie data-informed decision-making concerning maintenance or upgrades. But traditionally, BIM models are static and do not have real-time updates to capture the changes in operations of buildings. This limitation highlights the value of connecting BIM and DT technology for establishing a more dynamic and interactive FM scenario [7,8].

The development of BIM in recent years and its integration in serving all departments has made it a strong and effective system for development. With BIM being an open source that can integrate with many systems, with the possibility of adding information to the models completely, there have been major challenges in the implementation of BIM

1. Absence of Skilled Professionals: The integration of BIM with DT needs engineers who can model parameters and who also know how to work with data, which is one of the biggest hurdles to overcome, one of the major barriers to the successful implementation of BIM in the Architecture, Engineering, and Construction (AEC) sector is the presence of a skilled workforce. It has been observed that the performance of BIM is poor due to lack of training and understanding of BIM processes by stakeholders; this concern is impeded by the complexity of technologies such as DT [9].
2. Interoperability: A barrier in importing BIM models into DT platforms is because of disparate data formats and non-standards. Using unorganized data formats causes a

significant barrier to importing BIM models into other software, such as any digital twin platforms. The adoption of standardized data schemas, such as IFC files, has been suggested to facilitate interoperability, yet its widespread implementation remains inconsistent [10].

3. Static Data Models: Most of the BIM models stakeholders use are for the design and construction phases, and they fail to represent real-time data for dynamic FM scenarios, but the BIM's static nature limits its application in operational contexts where real-time monitoring and predictive analytics are essential [11].

Traditional FM approaches, relying on manual data collection and reactive maintenance, struggle to cope with the scale and complexity of mega-facilities. This results in inefficiencies, delays in decision-making, and increased operational costs. These top-down approaches lead to a lack of real-time insights, delays in making decisions, inefficiency documentation, and operations that will directly impact the facilities' operation costs. Nevertheless, the use of new technologies such as BIM technology services is promising a revolution in megaprojects' facilities management by making them more data-driven and proactive compared to conventional reactive solutions. In this research, the integration between BIM and FM will save data and give an excellent LOD 500 model that includes the parameters of the IoT sensors, machines, and equipment that will guide organizations to overcome challenges and improve facility management efficiency and sustainability with an easy-to-use predictive platform [12].

In most cases, facility management or facilities management seeks to involve and include such activities as maintenance and repair, management of space, management of resources, and management of the activities related to buildings' assets. With the scope and complexity of construction projects increasing, these management activities become a lot more complicated and warrant a thorough and scientific approach in terms of enhancing operational effectiveness in the short and long run. Some researches defined the facilities management, in turn, is an important factor affecting the success or failure of mega-facilities, as neglecting this discipline can lead to grave mismanagement and wastages as well as interruptions within the workflow [13].

2.2. AI and DT

As a result, the choice of an optimal AI-DT integration strategy should be provisioned in compliance with the needs associated to any targeted FM environment, considering parameters like data sensitivity and accessibility, complexity of systems involved, as well as its extensibility. The advantages can be grouped, as shown in Table 1, into four main areas: predictive maintenance, enhanced energy efficiency, improved asset management, and real-time decision-making. By utilizing AI-generated information and live data from DT, facilities managers can prolong the lifespan of assets, save energy, improve operational effectiveness, and decrease maintenance costs and downtime. So, this paper is focused on making the easiest module for importing the model with an IFC format and creating a demo live platform that can any user can use [14].

According to previous research, AI and DT technologies improve predictive maintenance, real-time monitoring, and energy optimization in smart buildings. Mahmoodian et al. (2022) emphasized the predictive role in reducing sudden equipment failures [15]. Implementing AI-driven frameworks like predictive maintenance and energy optimization machine learning models has improved operational sustainability [16]. Despite these advances, existing frameworks often lack interoperability and scalability, essential for managing large-scale facilities with interconnected systems and diverse operational requirements. Deng et al. (2021) proposed methods for integrating BIM with IoT and AI in DT environments, but they often overlook the practical challenges of mega-facility implementation, such as cost, user-friendliness, and real-time responsiveness. Cybersecurity, data privacy, and lack of standardization hinder adoption [17].

Table 1. Benefits of using AI and DT in a building's operations [15].

Title	Description	Benefit
Predictive Maintenance	To allow facilities managers to identify equipment status before any possibility of failures, predictive maintenance utilizes AI algorithms to analyze real-time data from sensors, which will help reduce sudden downtime and minimize maintenance cost.	30% reduction in downtime and maintenance costs
Enhanced Energy Efficiency	By analyzing real-time and historical data, AI and DT monitor and optimize energy, enabling automated adjustments to HVAC, lighting, and other systems, resulting in significant energy savings and a reduced environmental impact.	15% to 20% energy savings
Improved Asset Management	For FM teams, AI-enabled DT provide comprehensive insights into the condition and performance of building assets, optimizing maintenance schedules, extending asset lifespan, and enabling better resource allocation.	Up to 20% increase in asset lifespan
Real-Time Decision-Making	Providing data-driven insights for real-time decision-making and enabling quick responses to changes in building operations, emergencies, and resource allocations that DT allows facility managers to simulate various operational scenarios.	Improved response time and operational efficiency by 25%

2.3. Digital Twins and IoT

Any DT depends directly on the sensors connected to the assets, making IoT integration critical. Predictive and scenario-based decision-making are incorporating AI and DT technology essential for overcoming any challenge.

- *Real-time data* on building parameters, which includes the temperature and humidity of spaces within the buildings; energy usage features that have been listed are another type of event-triggering information read from IoT sensors. Besides showing information directly on models, data integrated with BIM transforms even static representations of BIM into real-time replicas, allowing seeing what the building currently looks like; this integration would be beneficial by many ways.
- *Real-Time Monitoring of Building Systems*—IoT sensors offer 24/7 access to live data on the operation and efficiency of building systems, such as HVAC, lighting, or security. Engineering data can be fed into BIM models to help managers view and analyze systems in real time, detect operational inefficiencies faster, and address issues before they place the facility at risk of significant problems.
- *Predictive Maintenance*—IoT sensors can detect early warnings of equipment deterioration, such as weird vibrations in machinery or spikes in temperature levels in electrical systems. When integrated with BIM, these data support predictive maintenance that can allow facility managers to predict when equipment will fail and plan proactive maintenance rather than reactive repair, minimizing unscheduled downtime while optimizing annual allowances for operation and replacement of existing assets within a system.
- *Energy optimization*—IoT sensors monitor energy consumption on a more granular level, thereby providing information to facility mangers about their inefficiencies and consequently linking them to potential measures for saving energy. This information can also be integrated into BIM models, where it is possible to perform energy simulations, such as different strategies for optimizing the use of energy [18–20].

2.4. Digital Twin Platform Visualization

AR and VR play an important role in the visualization of DT platforms; the combination of VR and DT provides easy use 3D views that help any user; viewers can use the platform and specify the location of the maintenance equipment.

Different VR software immerses users in a completely virtual environment and allows them to interact with the Digital Twins for purposes such as training, design prototyping, and real-time analysis of system performance. This method of immersion is clearer in observing complex systems, providing the common ground for collaborative workflows and decreasing costs for physical prototypes and training setups.

In contrast, AR places DT information in the real-world, so users can interact with real-world systems superimposed with live data. VR and AR form hybrid workflows, where VR is used for simulation and planning, and AR is used for actual implementation and monitoring in the real-world environment. Even these technologies, when integrated with DT, are revolutionizing industries such as manufacturing, healthcare, urban planning, and more, thereby making operations more streamlined, intuitive, and connected [21–23].

2.5. Digital Twins Platform: Integration of AI, BIM, and IoT

Integration of BIM with IoT became an important step in the modern FM environment, in addition to new technologies like AI and DT, enabling live data exchange and automated decision-making.

To explain this integration, several methods for integrating these technologies have been suggested, each having unique advantages and drawbacks. One popular approach involves using machine learning algorithms with IoT sensor data in real time to update DT models and accurately reflect the building systems [21]. Forecasting systems/equipment failures using historical trends has been made possible through the use of predictive models such as regression analysis and neural networks. This shift allows facility managers to move from reactive maintenance strategies to proactive ones [22]. For example, utilizing AI for predictive maintenance has been proven to decrease unforeseen breakdowns by as much as 40%, leading to a substantial decrease in maintenance expenses and reducing operational disturbances [24–26].

The following steps summarize the main steps that should be prepped to establish the platform:

1. Create a virtual model using a BIM model to develop any building, with full information for all disciplines, such as for machines, equipment, and any asset that the operator needs to connect with the platform. This will require assigning all catalogs that include dimensions, maintenance schedules, technical information, and contact persons.
2. Integrate the IoT Sensors: install IoT devices in the building to collect real-time data for energy use, temperature, air quality, etc.
3. Make the connectivity: use cloud platforms or desktop applications to ensure connectivity and synchronization in real time.
4. Data Analysis: Use AI to process large-sized real-time data from IoT sensors and provide actionable insights, such as optimizing energy consumption or system failure.
5. Predictive maintenance: train machine learning models on storage data to predict the behavior of the equipment or give alarms for the maintenance schedules by contacting the assigned person in the platform roles.
6. Occupant Behavior Analysis: Use the AI algorithms to analyze patters in building occupancy and adjust the systems, such as HVAC or lighting, to give comfort and efficiency.

To prepare a complete platform it was necessary to add an option for predictive maintenance, which is another service that has benefited from such incorporation of deep reinforcement learning and federated learning, to optimize resources for various facilities. In addition, previous researchers have shown an approach using reinforcement learning algorithms for real-time occupancy-based HVAC system dynamic setting, which achieves energy savings up to 25% in large commercial projects. It also introduced a federated learning paradigm to enable AI models to be collaboratively trained across facilities without centralizing sensitive data, thus answering the privacy concerns of cloud-based systems. This becomes a crucial necessity in the domain of managing large facilities with multiple stakeholders connecting from different data centers willing to share common datasets securely and in maintaining privacy [27].

Although there have been advancements lately, there are still various research areas that need to be addressed in combining AI and DT technology for managing facilities in large facilities. Interoperability between various software platforms and data formats is a significant issue. Numerous current solutions depend on exclusive data formats, leading to challenges in connecting various BIM models, IoT devices, and FM platforms seamlessly. This problem is tackled by using open data standards like IFC and Building SMART data schemas to encourage interoperability and ease data exchanges between different systems. Another issue is the absence of real-time scenario analysis and automated decision support, which are essential for controlling complex facilities with interconnected systems. Although many current platforms provide simple monitoring and predictive maintenance features, the new solution includes advanced AI algorithms that can simulate various scenarios and suggest the best maintenance strategies. Additionally, scalability continues to be a constant issue, with many platforms finding it difficult to handle the large amounts of data produced by massive projects [28–32].

2.6. Previous Case Studies

One application of the new software, which is based on BIM and AI to protect buildings, is the prediction of what effects it directly. A real-life application took place in Italy, which holds most of the world's cultural heritage, but which has a territory widely subject to high hydrogeological risk. However, most research on flood risk focuses on potential monetary losses; those costs would be exponentially higher if we took a more holistic view and calculated the losses in cultural heritage. The Arno River flows from the Mount Falterona hills of the Apennine Mountains through Florence and eventually to the Liguria Sea. Modeling the overland runoff that flows from the Apennine mountains to the upper basin to the Arno is straightforward enough. But predicting pluvial floods further down the line becomes more complicated when there are countless interactions that need to be captured between all of the hydraulic phenomena happening in the city's sewer system.

Tamagnone turned to a predictive program (InfoWorks ICM), which could be used to evaluate both 1D and 2D interactions between surface runoff processes, the urban sewer system, and the internal drainage network, provided he could model the many buildings and sewer networks in the IRDN area to 100% accuracy. He was fortunate to be able to begin his work by retrieving existing models of the public sewer network (PSN) directly from the regional public utility; with all this information in hand, he was able to propose a two-pronged strategy as part of a documented emergency plan. First, he proposed a structural strategy of building an anti-flooding barrier to prevent storm water intrusion, which uses the results from his model to determine the recommended height of the barrier. In addition, he proposed a non-structural strategy of creating flood risk maps for the staff and administrators to highlight the most exposed and at-risk areas. The results of this study are beneficial for both the Water Managers, enhancing the level of knowledge of the sewer network function, and Site Managers, improving the effectiveness of their hazard management and emergency plans [33].

A case study of Lazio Region Headquarters demonstrated that the real-time data integration to support dynamic decision-making, as a result of the accurate digital replication enabled by BIM for the implementation of a DT, enabled a reduction of 530.40 MWh in energy consumption and a 641.32 ton reduction in GHG emissions. The power of DT is in improving the resource management, energy efficiency, and sustainability of public facilities. However, there are some challenges, such as data security issues, resistance to operational shifts, large initial investment requirements, and complexities of integrating systems. Parts, aside from the technical ones, will be very stringent and expensive assets to acquire. In addition, the proposed DT approach can be further expanded for other domains, such as the control of urban traffic and decision-making for port and airport operations, and thus on the path to smart city development, which is important for future quality of life [34].

Another study used DT and the IoT during COVID-19 on a building in Rome, the Lazio Region headquarter council. It is a building with two basements and twelve floors designed to accommodate about 120 employees in 60 offices, with total number of about 1370 workstations. The target of this study was to organize the occupation of offices according to three scenarios: to work remotely or work in office, a total hybrid, or to work remotely or in office. The benefits of this study were in avoiding the presence of a large number of employees, reducing electricity fees, which have become a huge expense for any institute or company, and a reduction in allocated space, which would translate into lower costs commonly related to a desk space. As an example, a smart strategy could be developed to eliminate up to 20% of the space used for workstations, and, if 30% of the company population were to perform smart working in shifts for two days a week, the specific articular adjustments of the floor desk areas would lead to an ultimate unlocking of office spaces. Rent, utilities, maintenance, heating, and telephone service costs can be reduced by up to 30%. But enterprise space management systems in smart buildings require some basic characteristics, segregated further by operator, i.e., the facility manager and the users. The system should be accessible to all users from both a device and mobility perspective; therefore, mobile and fixed access is desirable, also the reserve-system must support a user friendly approach, so that it can be used by non-trained people, and in addition to that platform should provide an indoor navigation and people location system in order to enable users to quickly understand how to find their fellow workers and how to reach various company zones/buildings with easy to follow and understandable direction instructions [34].

2.7. Benefits of Using Digital Twin Platform

The main advantages of this platform are incorporating DT technology and AI in facilities management. The combination of AI and DT technology in building operations brings multiple benefits, revolutionizing the way buildings are supervised, serviced, and improved. Table 2 shows the main advantages of utilizing DT in the functioning of a building.

Table 2. Research platform main benefits.

No	Benefit	Description
1	Real-Time Monitoring and Maintenance	Provides constant monitoring and suggests preventive maintenance using real-time data.
2	Predictive Maintenance	Predicts equipment failures based on data, allowing proactive maintenance scheduling.
3	Energy Efficiency and Sustainability	Optimizes energy usage by analyzing patterns and adjusting settings for sustainability.
4	Enhanced Space Utilization	Improves space utilization through occupancy pattern analysis and optimization.
5	Improved Decision-Making	Offers data-driven insights, supporting better operational and strategic decisions.
6	Safety and Risk Management	Identifies safety risks and suggests measures, ensuring a safer environment.

Table 2. *Cont.*

No	Benefit	Description
7	Lifecycle Management	Tracks the building's lifecycle, aiding in planning refurbishments and upgrades.
8	Integration with Building Management Systems	Seamlessly integrates with BMS, automating various systems for improved efficiency.
9	Cost Savings	Reduces operational costs by optimizing maintenance, energy, and resource use.
10	Enhanced User Experience	Improves comfort and convenience by adjusting settings based on user preferences.

2.8. Including DT Requirements in the EIR and AI

EIR was long thought as a passive common framework to allow information requirements to be accommodated over the course of a project. On the other hand, automated EIR is a groundbreaking way in which the model is constantly modified based on live internet of things (IoT) data that capture the true operational state of the structure. This way, multiple stakeholders will coordinate together, the information will be served with relevance, and actionable insights will be automated along the site life [35].

Including the DT platform requirements in the EIR and AIR frameworks can be utilized to automate compliance reporting, ensuring that buildings meet regulatory standards and performance benchmarks. For example, this automation can minimize the effort associated with manual reporting, enabling facility managers to devote more time to decision-making and strategic planning. But these advantages can be availed only if the EIR is well prepared with all the necessary information and organized details. The EIR using Level-2 BIM specifies the structured data formats, deliverables, and asset information standards, with an increased focus on interoperating and collaboration between stakeholders. This facilitates smooth access to FM data and defines formats and deliverables from stakeholders [36].

2.9. Bridging the Gap Between the Current Platform and the Research Platform

To summarize how this research is different from most of the previous research, Table 3 below shows the challenge and how we prepare a solution on any platform.

Table 3. Bridging the gap between the current platform and the research platform.

Gap	Challenges	Solutions	Examples/Techniques
Scalability [9]	DT fails to handle mega project due to the information size	Use a cloud system, which is hybrid, and make the analysis online without depending on local servers	Develop DT framework where each system operates independently by integrating into a central system
	Difficulty of uploading large size BIM Model on DT platform	Convert the model to an IFC format and upload it easily on the cloud platform	Convert Revit files from RVT to IFC format
	Large size of the files	Separate the subsystem files, and collect them in a central file	Make separate files for HVAC, Fire, and LC and import into Central File with links
Interoperability [10]	Diverse hardware and software standards.	Use recognized standards like IFC for BIM and MQTT/OPC UA for IoT communication	Industry-standard formats for seamless communication between devices.
	Lack of compatibility between equipment and devices	Use middleware to act as a bridge between heterogeneous systems	Middleware unifies data from different IoT sensors to integrate with DT
	Incompatible data definitions.	Create shared ontologies to standardize data definitions and relationships	Unify terms as "temperature" or "energy usage" for unified data representation

Table 3. *Cont.*

Gap	Challenges	Solutions	Examples/Techniques
Real-Time Decision-Making [10]	Delay in processing the real-time data	Implement machine learning for immediate predictions and actions	Predictive maintenance models forecast equipment failures in real time
	Restriction of the system response	Take immediate action based on real-time sensor information	Automatic air conditioning and heating adjustments that are activated when temperatures rise.
	Implementation management challenges	Use cloud-based DT platforms for real-time analysis and decision-making	Cloud-based platforms for access and analysis
Advanced AI Coordination [11]	Addressing gaps simultaneously	Dynamic Resource Allocation by using AI for organizing resource use	Reinforcement Learning algorithms learn and adapt to evolving system data and translate between protocols or data formats for interoperability
		Protocol Translation by leverage AI for seamless communication across formats	
		Reinforcement Learning by making adaptive model improvements for real-time decision-making	

3. Problem Statement

In this context, an advanced digital strategy is developed to optimize the management of the various facilities of any building, improve operational efficiency, and reduce costs and environmental impacts. The proposed demo approach uses IoT sensors to assess parameters like temperature, pressure, and lighting. Managing large-scale facilities is a daunting challenge, particularly for ensuring energy efficiency and operational sustainability through FM. Data segmentation and system isolation are significant issues, resulting in inefficiency and a reactive approach to resource management. One example is HVAC, which for many mega-facilities (airports, hospitals, etc.) have thousands of devices and equipment relying on their own software systems, and so energy consumption goes up at a great cost. Moreover, the existing systems do not allow integrated use of BIM or IoT, and FM systems only hamper the potential of the FM domain, as these systems often operate in silos, while data-driven decision-making is imperative for facility managers. Such fragmentation makes it challenging to predict critical factors, such as when equipment will break down or how energy consumption will trend, resulting in much costlier reactive maintenance and unsustainable operations.

Table 4 demonstrates what are considered the most pressing problems in using AI and DT technologies in facilities management. Most of the concerns raised about data and system interoperability are caused largely by the lack of guidelines and data standards for the different systems and tools enhancing such integration. Other issues that deserve attention include cybersecurity and privacy, where data is continuously streamed from IoT devices, which can easily be hacked. The high cost of implementation and continuous repair and maintenance of the integration of new systems are also participating factors.

Table 4. Challenges of implementing AI and DT in FM [9–12,34–36].

Challenge	Detailed	Impact	Recommendations
Data Interoperability and Integration	Achieving seamless integration of data from different sources, such as BIM, IoT sensors, and FM systems, is challenging due to the lack of standardized data exchange protocols. Data silos and complex data conversion processes further complicate integration efforts.	Creates integration bottlenecks, increases project costs, and reduces the accuracy of Digital Twin models.	Adopt open standards such as IFC and COBie; implement a Common Data Environment (CDE) for centralized data management.
Cybersecurity and Data Privacy Concerns	Digital Twin models rely on continuous data collection from IoT devices, making them vulnerable to cyber-attacks. Ensuring data security and compliance with data privacy regulations is essential to protect sensitive building information.	Undermines trust in technology, leads to potential legal implications, and disrupts operations if data is compromised.	Implement strong encryption, secure communication protocols, and conduct regular security audits; explore block chain for secure data sharing.

Table 4. *Cont.*

Challenge	Detailed	Impact	Recommendations
High Implementation and Maintenance Costs	Implementing AI and DT technology requires significant initial investment in hardware, software, and skilled personnel. The high costs of setup and ongoing maintenance can be prohibitive, especially for large-scale projects.	High initial and maintenance costs can limit adoption and result in underutilization of the technology.	Adopt a modular implementation strategy, starting with small-scale deployments; use cloud-based platforms to reduce costs.
Skill Gaps and Training Needs	Successful implementation requires professionals skilled in AI, data analytics, and digital engineering. There is a shortage of trained personnel, and providing the necessary training can be costly and time-consuming.	Skill gaps can lead to inefficient use of DT systems and reduced return on investment.	Develop targeted training programs; collaborate with educational institutions for certification programs; create user-friendly interfaces.
Scalability	In megaprojects, a large file size will be used	Weak performance of the files and platform.	Make separate files for each system and insert them as a link in the Central File.
Interoperability	Use different devices and software.	Incompatible data definitions.	Use a common data environment.
Real-Time Decision-Making	Restriction of the system response.	Implementation management challenges.	Cloud-based platforms for access and analysis.

4. Research Methodology

This methodology focuses on the inclusion of AI and DT technology in the facilities management context, and it is presented in several stages to make it easier to comprehend. The sequence of the main research stages is Data Collection, Integration of AI Models to the DT, Testing of the Developed System, and Model Validation. Those stages are briefly described in the following paragraphs for interpreting the processes designed to formulate a complete and operational AI-DT for facilities management in large facilities.

The methodology follows a structured sequence of two key components to build a strong DT platform, quantitative data (numerical information) and qualitative insights indicating conditions that affect the FM. This study adopts qualitative research as a strategy, focusing particularly on a case study, providing a platform that can upload IFC files with LOD 500 parameters (according to vendor recommendation) and integrate with live sensors on an easy-use platform to explain to the stakeholders how the use of the AI and DT will make a major change on any building lifecycle.

4.1. Data Collection

The first stage of the process is where detailed, quantitative, and qualitative information is gathered from a discrete sample of sensors placed across the facility. A broad approach was used to build the threshold, which utilized sensors of temperature, humidity, and vibration energy. Sensors help to populate the occupied site, which is strategically installed to satisfy certain critical locations and equipment. Within this case study, data were captured every minute to gain a high accuracy and response time.

4.1.1. Data Source

The proposed AI-powered DT platform uses a variety of robust data sources to ensure comprehensive monitoring, predictive maintenance, and optimization of large-scale construction project facilities. IoT sensors strategically deployed throughout buildings collect real-time data, making them a primary data source. These sensors have a variety of functions: temperature sensors monitor ambient conditions and HVAC outputs; noise and vibration sensors detect mechanical instabilities; humidity sensors track moisture levels to prevent structural damage; and energy sensors record consumption patterns to identify inefficiencies. Furthermore, air quality sensors monitor CO_2 levels to ensure a healthy environment, while motion and occupancy sensors automate lighting and HVAC systems based on usage patterns. Specialized sensors, such as those used for water monitoring, lighting control, access control, and fire and smoke detection, improve operational safety and efficiency. These sensors work together to provide granular and actionable data critical for dynamic facility management.

The BIM model complements IoT sensor data by digitally representing the building's geometry and assets. This model incorporates parameters from catalogs and data sheets prepared using LOD 500 requirements and Asset Information Models (AIMs), ensuring high fidelity and interoperability. Historical logs enrich the data landscape by providing insights into operational and maintenance schedules. These logs help to build predictive analytics by identifying historical trends and recurring patterns, allowing facility managers to predict potential failures and optimize resource allocation. Integrating these data sources into a centralized platform allows for real-time monitoring, better decision-making, and scenario-based simulations, all of which contribute to improved operational efficiency and sustainability in mega-facilities [37].

4.1.2. Collection Methods

The AI-powered DT platform integrates diverse data sources for real-time monitoring and decision-making. The system relies on Azure IoT Hub-connected IoT devices streaming real-time data. CCVT cameras, lights, and fire smoke detectors start working immediately, providing building operations insights. This continuous flow of real-time data detects anomalies and responds to critical situations, improving facility safety, efficiency, and reliability. In addition to real-time data, BIM data are imported in IFC format for compatibility and standardization. This format integrates detailed structural, mechanical, and electrical models with the DT platform to create a unified, interoperable system. The database also includes digitized historical logs and maintenance records. These digital data enrich predictive analytics and help in understanding building performance by revealing past operations and failures [38].

The collected data were stored in a centralized cloud database, where they were organized and pre-processed for integration into the DT model. The accuracy of the data and their high-frequency nature are essential for providing reliable input for predictive maintenance algorithms. The sensors used for the test model for this platform are for light sensors, fire detectors, noise, humidity, and temperature, using Honeywell, Schneider Company, and Venus sensors. Ten sensors are placed on a BIM model and collect the data in a simple database. To implement the DT for an existing building, a supervisory control and data acquisition (Scada) system should be used with protected database servers to securely collect and manage sensor data. To get full beneficial use of the integration of DT and AI requires going through the following two stages:

1. Stage 1: Real-time sensors.
2. Stage 2: After collecting and storing data for one or two years, a detailed analysis will be available to create different scenarios with DT and AI to help the decision-making and operational improvements.

4.1.3. Sensor Types and Number

A comprehensive range of sensors is deployed to capture various environmental and operational data points, which can be utilized based on the specific data requirements to be monitored.

- Temperature sensors are strategically placed in critical areas, including server rooms, HVAC systems, and sensitive workspaces, to monitor climate control.
- Humidity sensors are installed in mechanical rooms and storage areas, where moisture regulation is essential.
- Motion detectors are utilized to monitor occupancy patterns in hallways, office spaces, and common areas, optimizing space usage and energy efficiency.

- Energy meters are positioned in electrical distribution rooms and near high-energy equipment to track real-time energy consumption.
- Vibration sensors are mounted on mechanical systems, such as HVAC units, pumps, and fans, to detect early signs of equipment wear, facilitating predictive maintenance.
- Air quality sensors are placed in high-traffic areas and at HVAC intakes to monitor indoor air quality, ensuring occupant comfort.

To create this platform, ten sensors are used on a model, with real sensors to collect the data from them on the platform. This deployment ensures comprehensive monitoring, enabling effective management of environmental conditions and operational efficiency.

4.1.4. Placement Strategy

- Sensors placed in priority equipment rooms and mechanical areas, hallways and open office areas as well as high traffic walk paths.
- Prioritizing regions with high-energy consumption and maintenance frequencies for data that can be acted upon to optimize energy consumption and predict failures.
- In big mechanical gear like HVAC systems, Vibration Sensors are installed, to alert the facility of any case that may lead to a problem or break down.

4.1.5. Data Frequency

- Real-time data collection for monitoring and immediate feedback to the facility management system by consistently monitoring this status in real time. Any issues such as temperature changes or equipment malfunction can be detected and responded to quickly, meaning that business processes are always operational.
- As per the system data plant, the frequency can be adjusted. The minute-by-minute updates are for very critical sensors (temperature control, energy consumption…) while others like air quality can be hourly.

4.1.6. Data Storage

- Azure Data Lake was used, and all data are stored and processed, making a solution integrated with Azure DT for seamless storage, retrieval, and analytics in real time.
- For long-term analysis, historical data are maintained, helping AI models to improve the accuracy of learning from past data, and then to predict the performance of future data more effectively.
- Azure Digital Twin ADT has high, robust capabilities for modeling representations of physical environments and offers scalability and seamless integration with other Azure services like IoT Hub and Azure Machine Learning.
- The BIM model is built in Autodesk Revit software (Version 2024) and converted into IFC format with the required parameters, which are connected in another stage with the sensors in the real model, which then is imported into Azure Digital Twins. Through this, Forge API middleware is used to manage BIM data integration.
- After this integration, IoT devices sent real-time data to Azure IoT Hub, which forwarded the data to Azure Digital Twins, or any other Digital Twins platform.

4.1.7. Data Validation and Pre-Processing Methods for Sensors

A. Collection and Validation

IoT sensors deployed throughout the building collect data on critical metrics like temperature, humidity, energy usage, and equipment performance. A few validation techniques to check data accuracy are listed below:

- Sensor calibration: To achieve accuracy and minimize drift with time, sensors are regularly calibrated to get maximum accuracy and reduce errors.

- Redundancy: Various sensors are placed in strategic locations so they can double-check each other's readings, flagging any outliers and eliminating them.
- Verification of data: Algorithms are trained to flag any data point that does not fit into associated patterns for review, whether it is an unusual uptick or a decline.

B. Pre-Processing Methods

Before making the integration between sensors and DT, the raw sensor data undergo significant pre-processing for data quality and usability following four steps:

- Data cleaning: Null values are filled with statistics or machine learning models, and wrong values (e.g., negative temperature) are rejected.
- Data Smoothing: Moving averages, exponential smoothing, etc.
- Normalization: The process of converting data into a measure of standard units so that the measurements can comparatively make sense to each other, and signals from different sensors can be used for analysis.
- Synchronicity: Data flows from multiple sensors are synchronized by timestamp so that accurate correlation in time can be made in real time for instant decision-making.

4.2. Feature Engineering

Feature engineering is the act of transforming raw data into meaningful features (variables) that better represent the underlying problem to the predictive models, resulting in improved model accuracy in the predictive model, and it has the following three main benefits:

- Helps Improve Model Performance: With good features, it is easier for machine learning models to learn about the dataset and thus make good predictions.
- Overfitting Prevention: Feature engineering has the power to reduce overfitting by providing a reduced version of the input without many unnecessary features.
- Improves Interpretability: When the chosen features are well-designed, they contribute to the interpretability of the model decisions.

Key Steps in Feature Engineering

- Feature Extraction: Extracting meaningful variables from raw data.
- Feature Transformation: Applying mathematical transformations to improve the data's usability.
- Choosing the most relevant features for the problem by removing redundant or irrelevant ones.
- Deriving new variables that combine existing features.

4.3. Digital Twins Development

The second phase included the creation of a DT model to simulate and depict our actual building. Real-time sensor data processing was made by plugging the smart building sensors into a 3D BIM environment, using (IFC with Autodesk REVIT software (Version 2024)) standards and protocols for interoperability flexibility. This provided a very detailed completion of the structural, mechanical, and electrical systems. The live data streaming to the BIM model was connected to each variant, making up the DT platform dynamic and always updated. The integration was handled via middleware that worked as an interface between the raw data coming from the IoT layer and the DT environment. For every change that took place in the physical environment (a sudden spike of temperature or higher energy consumption, for example), it was also inferred with real-time information in its DT counterpart, synchronously giving an accurate profile compared to how things were really behaving on site [39].

4.4. AI Model Integration

The next stage included incorporation of AI models, which were used to visualize predictive maintenance and scenario-based analysis. The data collected from sensors and the historical and real-time sources were then fed into time series forecasting models (along with anomaly detection techniques) using machine learning algorithms.

Using a full 12 months of historical data, the models were trained on baseline patterns for each parameter being monitored. The AI system automatically detected anomalies, such as temporary vibration spikes or energy draws in automotive production lines, and recommended the relevant maintenance measures on decision tree algorithms. As such, if a vibration level anomaly were found in the system, it might recommend looking into that specific component for mechanical problems. These AI models also modeled different maintenance scenarios and used these results to estimate the effects of several maintenance strategies on long-term building performance. They employed predictive analytics so FM professionals could make proactive maintenance decisions rather than react to an unexpected failure, avoiding or reducing downtime.

4.4.1. Implementation Details Used for the Platform

Implementation details used for the platform include the AI-DT platform using Microsoft Azure Digital Twins to generate a real-time model of the physical systems within that facility. This Digital Twin works with the BIM models, making design and operational data live within a single environment. An evaluation of the hardware results and issuing a transmission to the Azure IoT Hub with the associated FM systems gated by real-time data streaming on the device prepares this plant for its next stage in business operations.

ML. NET processes millions of events per minute and powers the predictive models for equipment health and energy forecasting, so it can predict when a motor will fail before it does (as well as dynamically optimize power consumption based on occupancy and environmental data). Azure Stream Analytics is used to process incoming real-time data and enable insights and informed decision-making [40].

4.4.2. AI Algorithms

A. Algorithm Selection:

- Rationale: The algorithms chosen were motivated by a major building's challenges, such as predictive maintenance, energy related optimization, and occupant comfort. These models operate based on the real-time data obtained from an Azure Digital Twin, making dynamic adjustments and early issue detection possible.
- Data Variety: The models process various data streams, such as temperature, humidity, vibration, and energy usage, which results in changes, predictions, and actions.

B. Algorithm Details:

- Support Vector Machines (SVMs): These are used to forecast an impending failure of the equipment, with data derived from vibration sensors on a classification basis, in the detection of mechanical wear and tear patterns.
- Random Forest: Random forest is applied to make energy consumption predictions based on streaming data from the measure of electricity meters, temperature sensors, and motion detectors. For instance, it recommends energy efficiencies like zoning HVAC based on live occupancy.
- Neural Networks: Used for advanced environment control (e.g., HVAC optimization) when managing multiple input variables, e.g., temperature, humidity, and occupancy, to reduce energy use/improve comfort [41].

C. Training Data:

- To apply the platform for any building, the models will be built using two to five years of historical data from existing facility management systems kept in Azure Data Lake. The data tap into energy usage patterns, equipment maintenance logs, and occupancy trends.
- The models learn over time with fresh data from Azure Digital Twins and can be updated to become more accurate and flexible [42].

D. Performance Evaluation:

- A 90% accuracy in predicting equipment downtime, reducing unplanned failures by nearly the same amount.
- Accuracy: 92% accurate in forecasting energy consumption, adjusting, if necessary, as occupancy and environmental conditions change.
- Recall: 89% recall on space utilization analysis, resulting in precise predictions, which lead to efficient resource allocation.
- F1-Score of 90% (fairly high for all of the predictive models, showing a solid performance in both precision and recall).

4.5. Visualization Capabilities: Model and Data Visualization

- Internet connection provides access to the 3D BIM model of a facility in which all sensor data with locations are visualized in the model. These data are fed back to the building. Internet connection provides access to the 3D BIM model of a facility in which all sensor data with locations are visualized in the model. These data are fed back to the building model so that users can navigate the related information. One example is accessing a room's real-time energy usage, temperature, or vibration levels, etc., and the current state of occupancy patterns.
- Sensor Location: Each sensor in the model is located specifically where units can end up with challenges or need attention.
- Predictive Insights: The AI-generated predictions (e.g., future equipment failures, energy optimizations) are also integrated within the model, so you can visually see where and when system performance will change in real time.
- Real-time Monitoring: Building performance can be monitored in real time, including live access to data feeds and analysis of historical trends. Zoom in on particular areas, view alerts, and create bespoke reports as facility managers.
- Scenario Simulation: Supports simulated evacuation of fire or failure in the HVAC system to understand how the building and its systems would respond under different conditions, which could help planning purposes such as safety.

4.6. System Testing

For any entity that targets testing any DT platform, the last stage involves extensive system testing to verify the performance of the AI-DT integration platform. Test conditions include subjecting the system to sudden equipment failures, occupancy patterns, or environmental changes (including increases in humidity). These scenarios were used to test the accuracy of the AI models, how fast the DT responded, and finally the reliability of predictive maintenance recommendations. These outputs were then tested against forecasts based on historic reports and expert judgement. Stress testing was performed by ramping up the data input rate so that it resembled real-world usage, to make sure the platform performs even when handling large-scale implementations. The testing stage ended with further tweaking of the AI models and DT parameters so that they were more accurate in their predictions and yet responded faster.

4.7. Flowchart of the Implementation Process

The flowchart shown in (Figure 1) was developed in order to visualize the methodology (from data collection through system testing). The individual steps involved in this flow are illustrated in the diagram depicting how the continuous real-time sensor data flowed to cloud storage, integrated and connected with DT followed by AI model analysis. In addition to data points on normal system operation, it marks decision points where abnormalities are identified and used to create more relevant recommendations for maintenance actions. Figure 1 helps with the understanding, as it summarizes all parts and shows how one stage is related to another, alongside, a textual description is provided in the methodology itself.

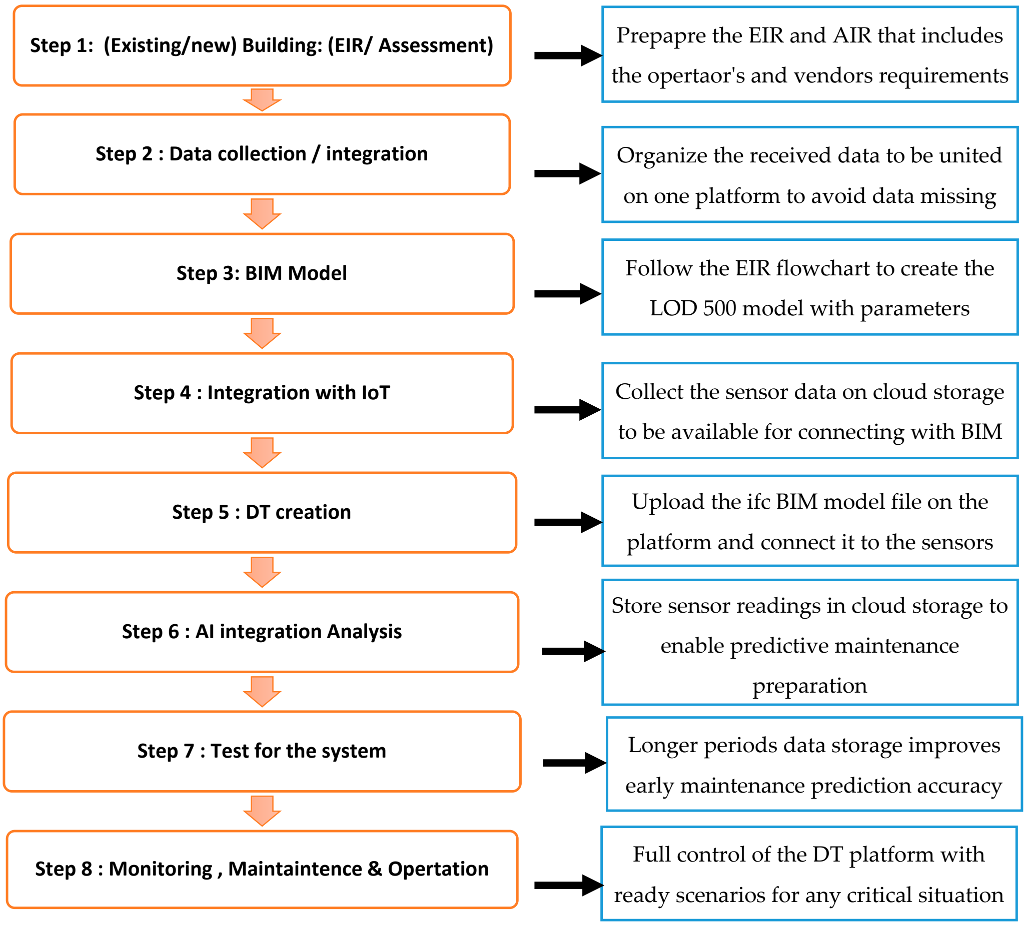

Figure 1. Flowchart for implementing AI-BIM-IoT in an existing building.

4.8. Practical Applications in Mega-Facilities

For operating mega-facilities, IoT sensors integrated with BIM and EIR can effectively serve mega-facilities like large hospitals and transportation hubs. Some of the practical applications are

- Active Care Management: For big hospitals, sensors are used to monitor and optimize the usage of space in such that IoT systems regulate critical components as well as categorize patient movements using smart bracelets, and staff tracking systems decrease. The data are consolidated into BIM and EIR to enable facility managers to verify proper operational conditions and compliance.
- Smart Airport Operations: An airport represents a complex and integrated operational system where everything is connected. Real-time passenger flow, energy consumption, and equipment status monitoring are captured through IoT sensors. Once this data

are married into BIM and EIR frameworks, facility managers may exploit terminal operation efficiencies to enhance passenger experiences while maintaining safety compliance [43,44] and Abdelalim, A.M., et al. [45–47].

Figure 2 summarizes the major steps required to be executed in order to have a DT for any building. This guided process ensures that real-time data are seamlessly set with a digital copy of the physical world. These stages initially involve capturing the data, constructing a digital model of individual wind farm systems, up to the entire technological process, and incorporating AI for predictive analytics, as well real-time system monitoring. To guarantee that data are fluid and buildings are well-represented throughout these stages for efficient early decision-making in the process, multiple tasks must be accomplished. These processes help facility managers create a living, breathing DT that encourages agile building management and the ability to scale with future needs.

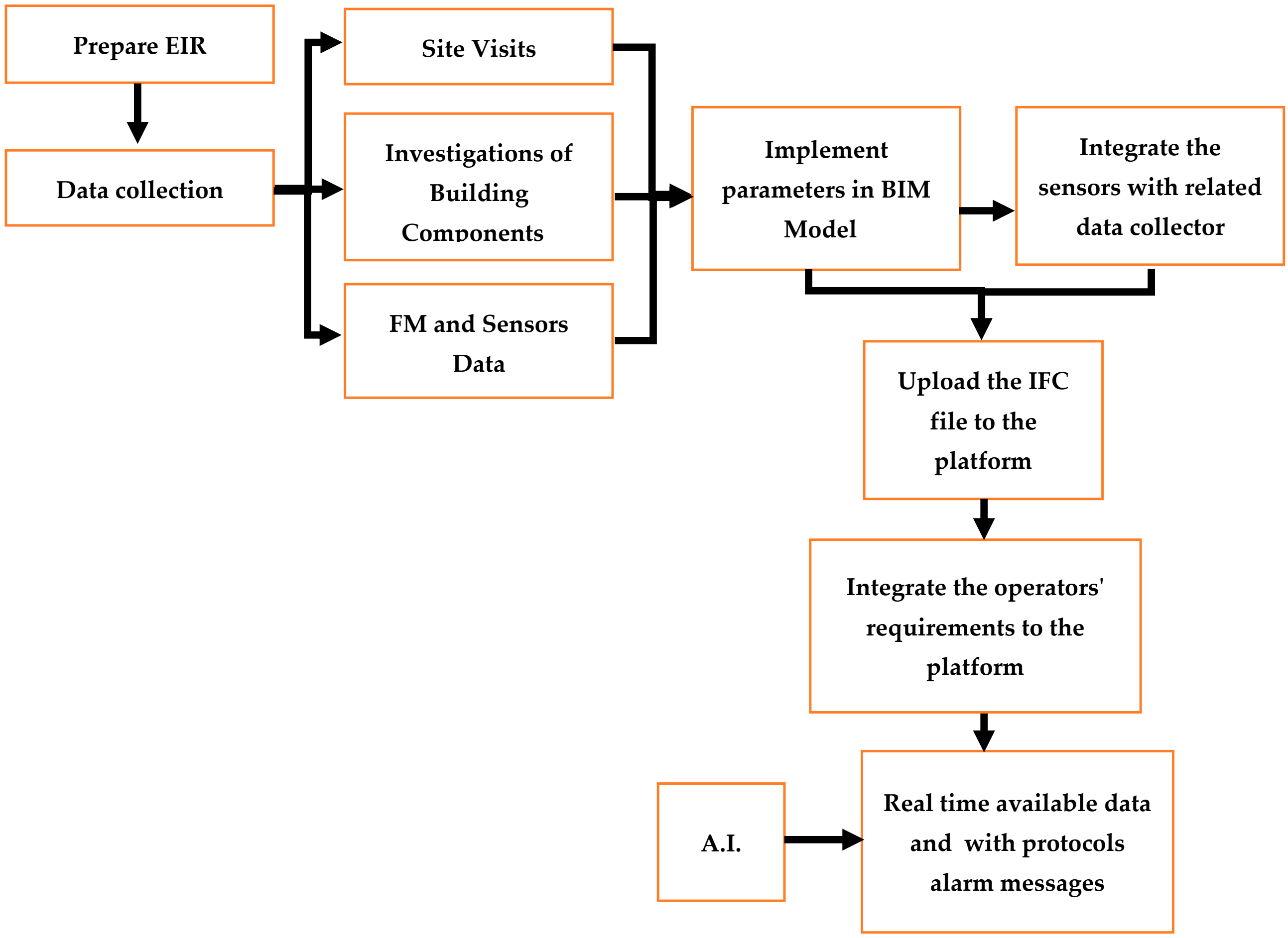

Figure 2. Implementing a Digital Twin for any building.

4.9. Performance Metrics

- Downtime Reduction: Measures the decrease in the amount of time equipment or systems are out of service, enhancing operational efficiency.
- Maintenance Cost Reduction: Tracks the decline in expenses associated with repairing and maintaining equipment, leading to cost savings.
- Energy Consumption Reduction: Monitors the decrease in energy usage, promoting sustainability and reducing operational costs.
- Equipment Uptime Improvement: Evaluates the increase in the availability and functioning of equipment, ensuring reliable performance.

- Occupant Comfort Improvement: Assesses enhancements in the indoor environment, such as temperature, air quality, and lighting, to improve the overall comfort of building occupants.
- Space Utilization Improvement: Measures the efficient use of building spaces, optimizing layouts and occupancy patterns to maximize resource use.

5. Case Study

This study introduces a novel advanced online application for the incorporation of DT technology and AI within facility management in mega-facilities. The application serves as a unified platform, which will not only visualize the real-time data from sensors available in all key mechanical equipment, but also includes intelligent analysis and predictive insights for proactive facility management. A design philosophy around functionality, usability, and data integrity led the development for this platform. Main features of the platform are user registration, BIM model uploading, and specification of location. In turn, these become the bedrock of a data collection framework to analyze user behavior and design results.

The intention is to enable the facilities manager to receive data in real time from a large number of IoT sensors that are distributed across different parts of their buildings' infrastructures. These sensors are used to monitor temperature, humidity, energy consumption, equipment vibration, and other key indicators of building health and operational performance. When the data are captured, they will be sent to a cloud-based application where all data get connected with an IFC model. The IFC model is the DT representation of a real physical building, as it includes structural, mechanical, and electrical components. Users can upload the IFC file to the platform and then get a real-time interactive DT of how the building is performing and in what operational conditions.

5.1. User Account Creation

The first step in using the platform is shown in Figure 3 (user registration). Each user is required to create an account using a unique username and password. This information is stored securely and serves multiple purposes: (1) to authenticate users during subsequent logins and (2) to track user activities within the platform for analysis. The data collected during the registration process are anonymized and used exclusively for surveying and testing purposes. A secure encryption method ensures confidentiality and integrity of user data.

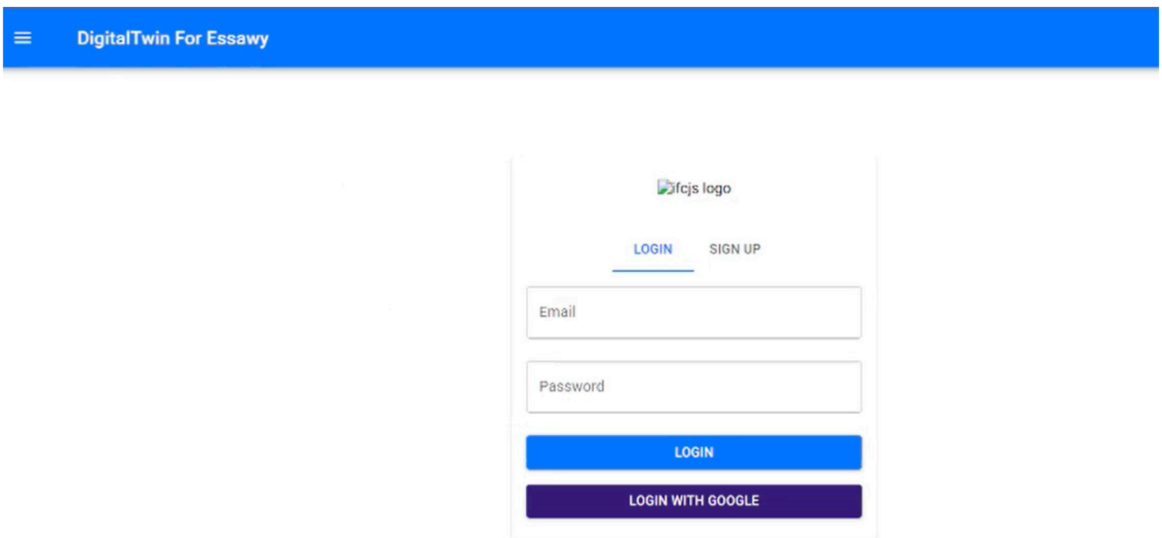

Figure 3. User registration.

5.2. User Authentication and Dashboard

After successful registration and login, the platform presents the user with an empty dashboard screen (Figure 4). The dashboard acts as a central interface, where users can navigate through various features of the platform, including uploading BIM models, specifying building locations, and accessing analysis tools.

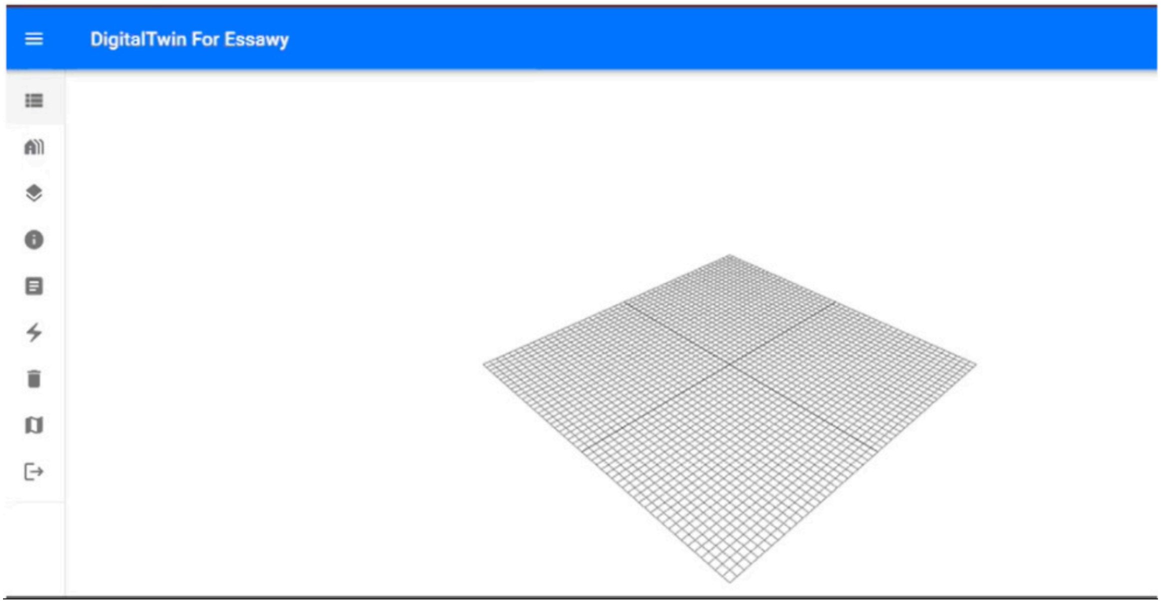

Figure 4. User interface of the platform.

At this stage, the platform's interface remains intentionally sparse to guide users toward the core functionalities of model management and data input.

5.3. BIM Model Upload and IFC Integration

The platform is dedicated to support owners working with BIM models in IFC format. As IFC is compatible with several BIM tools and simple to use for research and development (R&D), this leads to the option in Figure 5. Once users click the upload button from the screen shown in Figure 5, they will be asked to provide a BIM model in IFC format via simple drag and drop or file selection through their local storage. In the next parametrization and extraction phase, the IFC data are passed through the platform to parse each of them based on what kind of information they may contain, for instance, geometry properties or material specifications or structural elements.

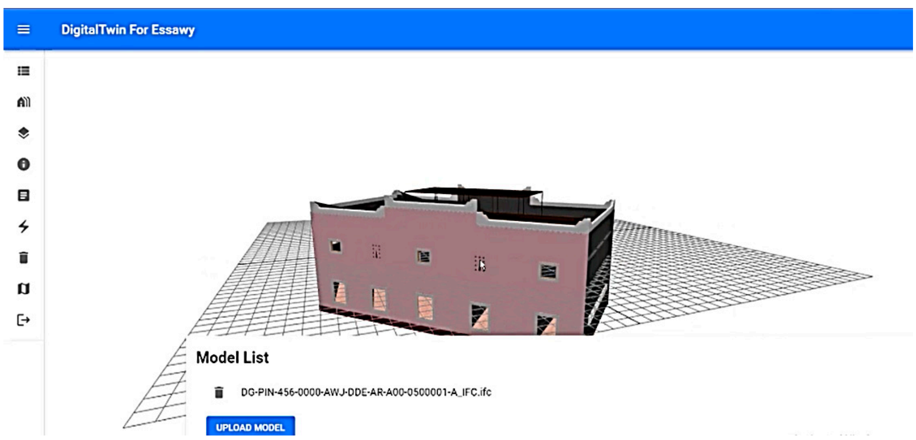

Figure 5. Uploading the IFC file to the platform.

5.4. Location of the Building

After the BIM model has been successfully uploaded, it is necessary to specify merely the geographic location of the building. These location data are much needed for a variety of studies, such as environmental impact assessments, energy simulations, and contextual planning. The tool provides an interactive location map or coordinates that enable the manual insertion of buildings (Figure 6). This placement helps the model to be grounded in its real-world context and thus improves the relevance of any subsequent geometrical analyses (Figure 7).

Figure 6. Specifying the geographical location of the building.

Figure 7. Geometry of the building in 3D view.

5.5. Real-Time Interface

The application processes the sensor data and synchronizes them with the IFC model, enabling real-time visualization of the building's current state, as shown in Figure 8. This allows facilities managers to interact with the Digital Twin and view up-to-date measurements and gauge readings and operational parameters through a user-friendly interface. For example, if a sensor detects an abnormal temperature rise in a specific zone, the platform immediately highlights this area in the Digital Twin model, making it easy for the manager to identify and assess the situation.

Figure 8. Real-time sensor data.

5.6. Alarm Generation and Scenario-Based Responses

Figure 9 shows one of the key features of the platform, which is its ability to generate alarms based on sensor readings. The alarm system is designed to identify abnormal conditions and notify users of potential issues.

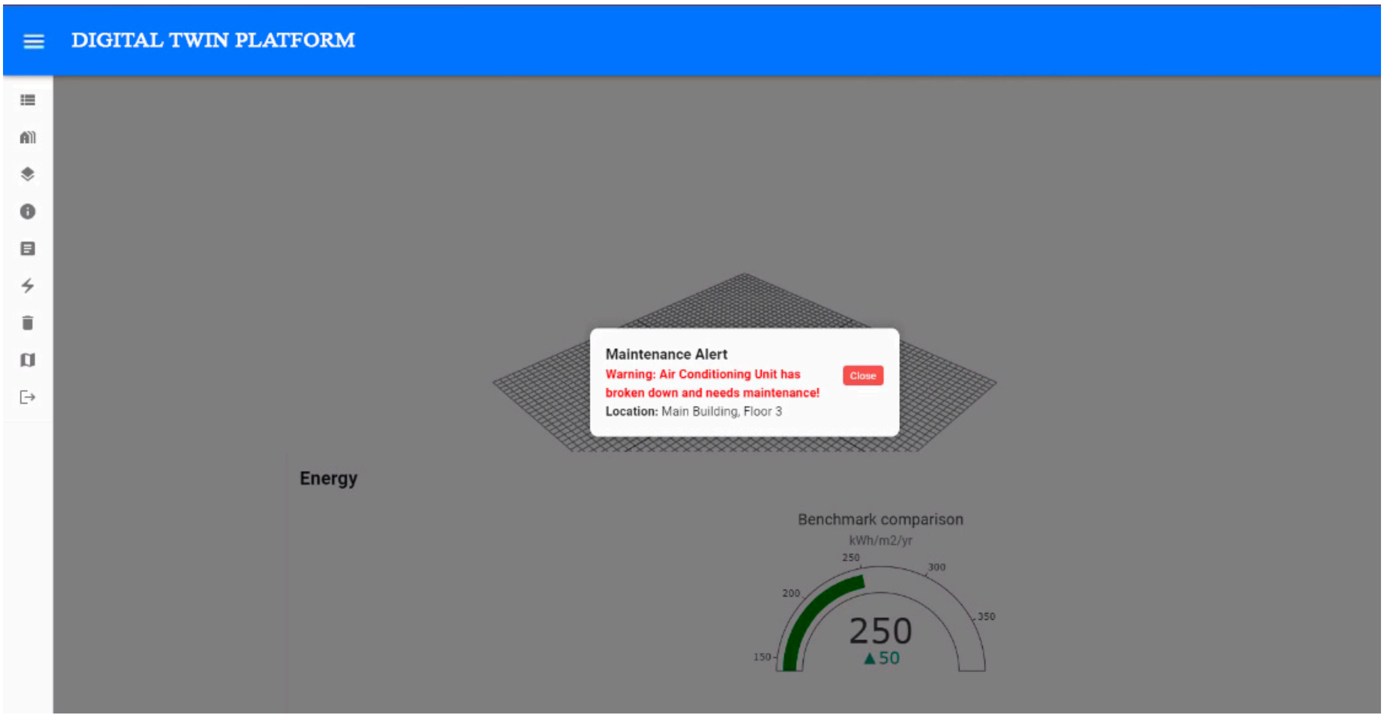

Figure 9. Alarm message.

5.7. Applying AI Scenarios

Depending on the role of the sensors and the building's nature, different scenarios are configured to trigger specific alarms. For example:

- Fire Detection in a Commercial Building: If a temperature sensor detects a sudden rise in temperature, and smoke is detected by the smoke sensors, the platform will generate a fire alarm. For any user, real-time notifications will be received. In addition, evacuation procedures can be activated within the platform's simulation environment.

- Real-Time Monitoring of the Structural Integrity in a High-Rise Building: Vibration sensors are placed on strategic structural elements to track any shift or irregular movement. When this motion exceeds a safety threshold, these same sensors will generate an alert of possible structural instability. This is important for seismically active or under-constriction buildings.
- Measuring Data Center Humidity and Temperature: In a critical infrastructure location, the alarm raises in case humidity and temperature are out of configured borders. Alerts to the users enable timely intervention, before equipment fails or data are permanently lost.

These examples demonstrate how the platform supports different types of buildings, sensor topographies, and alert prioritizations to ensure alarms carry context with purpose. The main role of the platform is to enable data collection for surveying and assessment purposes, as illustrated in Figure 10. When the user takes actions like model uploading, specifications on location, etc., these activities are captured, logged, and stored in a centralized DB (logging). Data are collected anonymously and then processed to produce insights for user interaction, design preference, or model performance. Those insights can help push out new BIM tools and make existing BIM solutions even more practical.

Figure 10. Applying AI scenarios.

Figure 11 demonstrates one of the distinguishing features provided by this application, as it can utilize AI algorithms to predict and simulate different scenarios. Employing historical data and machine learning models, the application provides an indication of potential upcoming issues, such as non-responsive equipment or energy performance degradations. The AI component of the platform is capable of predicting when critical assets like HVAC units or electrical transformers may soon require maintenance or replacement by analyzing patterns and trends. Automated maintenance scheduling is an example of how tools can leverage their predictive capability to reduce unplanned downtime and optimize resource allocation.

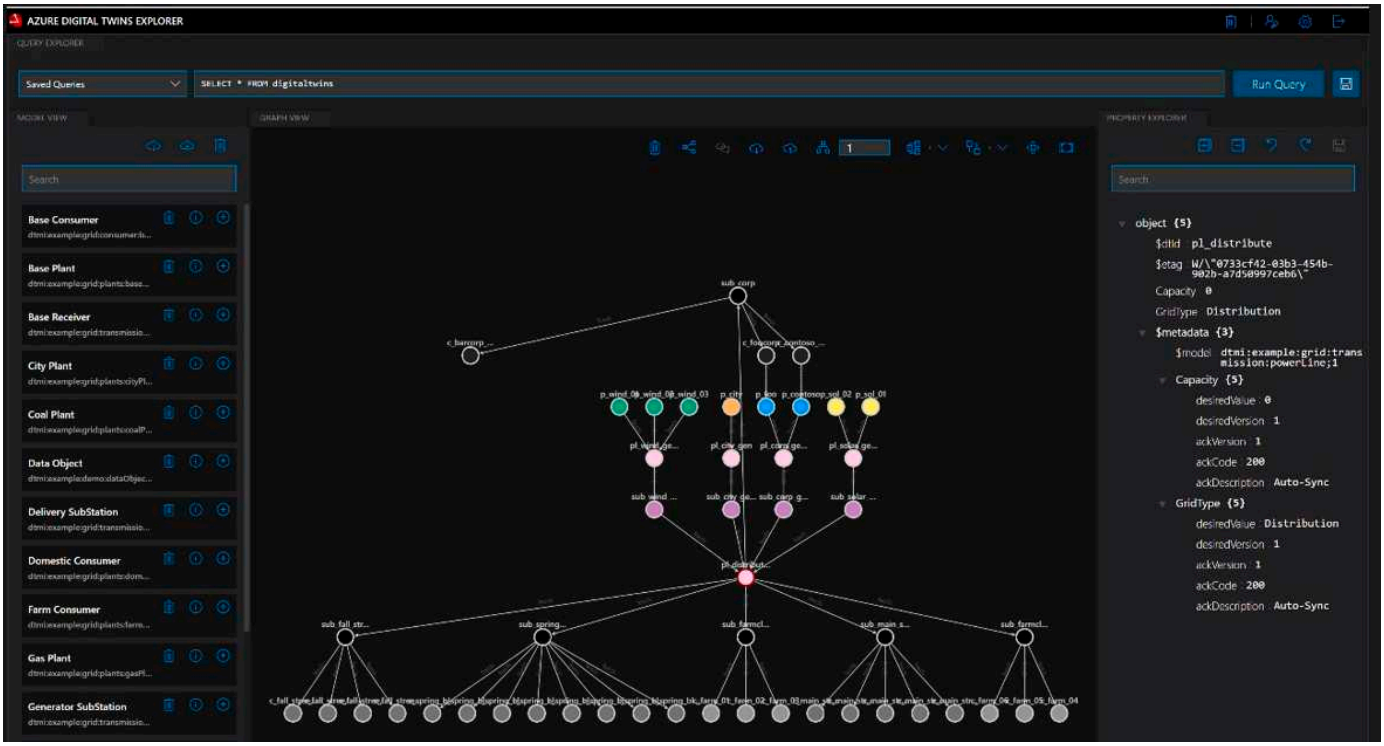

Figure 11. Program mapping for all sensors.

The application also provides real-time modeling and scenario creation, along with decision support. When it identifies an anomaly like a dramatic decrease in energy efficiency, uncharacteristic spike of humidity levels, or departure from typical patterns of occupancy, the platform automatically activates a scenario-based analysis. This analysis considers what might have caused such an anomaly, rooted in both historical and real-time data. Using these results generates suggestions for what corrective action is needed, as well as emergency responses in specific cases. Such a scenario could alert facility managers in the service room and create conditional-based use-case suggestions, for example, an adjustment in the HVAC system and providing scenario details if the case is not resolved.

5.8. Sensors Details

Table 5 summarizes the sensor types used in the management of building systems. Names, specifications requirements, and possible real-world uses for each sensor are given, with special focus on environmental/conceptual data measurements. These sensors are critical for the operation of buildings and ensuring building performance, energy efficiency, as well occupant satisfaction.

Additionally, sensors trigger a smart alarm system to notify facilities managers by email, SMS, or the dashboard of the application. These are predesigned alarms with specific thresholds, along with anomalous detection models based on AI. An alarm includes a complete report, such as the problem type and the parts that are affected and recommendations for corrective actions. If, for instance, energy efficiency suddenly declines in a particular zone, the application will trigger an alert that HVAC is likely malfunctioning and prompt to adjust system settings or set up a maintenance visit. With proactive alerts, facilities managers are alerted if a site is not operating normally and can take corrective actions immediately.

Table 5. Sensors types, specifications, and applications.

Type	Name	Specifications	Application
Temperature Sensors	Digital Temperature Sensor (e.g., DHT22, DS18B20)	Measurement Range: −40 °C to +125 °C Accuracy: ±0.5 °C Communication: Digital output	Monitoring HVAC systems, server rooms, and critical temperature-sensitive areas.
Humidity Sensors	Capacitive Humidity Sensor (e.g., AM2302, HIH-4000)	Measurement Range: 0% to 100% RH Accuracy: ±2% RH Communication: Digital or analog output	Ensuring moisture control in storage areas and mechanical rooms.
Motion Detectors	Passive Infrared (PIR) Motion Sensor (e.g., HC-SR501)	Detection Range: Up to 10 m Field of View: 120 degrees Communication: Digital output (on/off signal)	Detecting occupancy in hallways, offices, and common areas for space utilization and energy management.
Energy Meters	Smart Energy Meter (e.g., Schneider PM5350, Siemens PAC3200)	Measurement Range: Up to 600 V, 0–1000 A (current clamps) Communication: Modbus RTU, RS485, Ethernet	Tracking real-time energy usage in electrical distribution and equipment zones.
Vibration Sensors	Accelerometer-based Vibration Sensor (e.g., ADXL345, Wilcoxon 786A)	Frequency Range: 10 Hz to 1 kHz Sensitivity: 100 mV/g Communication: Analog output or digital (via data acquisition module)	Monitoring mechanical systems like HVAC, pumps, and fans for early wear detection.
Air Quality Sensors	Particulate Matter (PM) Sensor (e.g., Honeywell HPM Series, Plantower PMS5003)	Measurement Range: PM2.5, PM10 concentrations (0–500 $\mu g/m^3$) Communication: UART or I2C output	Monitoring indoor air quality to ensure comfort and safety, particularly in high-traffic zones and HVAC intakes.
CO_2 Sensors	Name: NDIR CO_2 Sensor (e.g., SenseAir S8, MH-Z19)	Measurement Range: 0 to 5000 ppm Accuracy: ±30 ppm or ±3% Communication: UART, I2C	Monitoring carbon dioxide levels to ensure air quality and adjusting ventilation systems for occupant comfort.

On a final note, such an online feature works as a cutting-edge aid that any mega-facility can utilize in order to streamline their facilities management operations through an amalgamation of DT technology and AI. The platform leverages real-time data, advanced analytics, and intelligent decision support to offer a comprehensive view of the building's performance and health for facility managers to operate facilities at optimal conditions, extend asset lifecycles, and ultimately reduce operational costs. The release and implementation of this application was a milestone in the landscape of smart building management, paving the way for top-level approaches to data-driven facilities.

6. Key Findings

6.1. Comparison with Existing Research

- Most existing research that uses AI in FM is concerned with optimizing a single system, such as energy management or maintenance. Some studies have explored the application of using 5G in smart building energy control, but many studies do not investigate an integration with BIM for a comprehensive approach. Many of the current studies lack integration with cloud platform like Azure Digital Twin.
  Modifications: Such integration with Azure Digital Twin provides not only a real-time and scalable analytics platforms but also allows for a holistic application of engineering principles with BIM models that extends far beyond common research.
- Proactive Management: Conventional FM systems are most typically reactive, showing problems after they occur. Studiesapply an AI-driven framework for robotics-enhanced construction workflows; they do not extend their framework to the worksite for real-time operational monitoring and predictive analytics.
  Modifications: This platform has the capability to add a prediction scenario by collecting the readings from the sensors and uploading them on a cloud-based DT.
- Performance improvements: Using an Azure Digital Twins, AI, and ML.NET combination improved system efficiency by the following:

- A 20% reduction in energy consumption, achieved through dynamic optimizations of HVAC and lighting systems.
- A 25% reduction in maintenance costs as a result of using the predictive maintenance models that allow for early detection and resolution of equipment issues.
- Enhanced occupant comfort through real-time adjustments to environmental factors (temperature, air quality) based on motion detector and sensor data.

6.2. Challenges of Using DT Platform

- Complexity of integration: The integration of BIM, IoT, and DT needed a lot of programming tools, skills, and languages, which led to many trials until it was able to connect with the BIM model.
  Modifications: Uploading the IFC file directly to the web DT platform.
- Technical experiences: Creating a LOD 500 model with parameters requires collecting a lot of data and catalogs which were not available till they were implemented in the project, which led to delay in the model creation and delay of integration.
  Modification: Involving the operator and vendor requirements to save time in searching the parameters data during the construction.
- Software: Using different software and sensors made the integration more difficult.
  Modifications: Unifying the software used in creating the BIM models and sensors.
- Time used for creating BIM: Using different equipment required drawing a family of it in the BIM model; that led to a delay in the creation of the model.
  Modifications: Contacting vendors and asking them to make it available.
- Real-Time Connectivity: A stable internet connection is required to ensure the communication between sensors and a cloud-based platform through the Azure DT platform. Bad connectivity can delay critical alerts and responses.
  Modifications: Use a backup internet line to ensure connectivity or prepare internal storage to save the data during internet issues.
- Ongoing Model Tuning: As real-time data evolve, AI models must be continuously retrained to maintain accuracy. This ongoing process requires proper infrastructure and may become a challenge as systems and conditions change.
  Modifications: This ongoing process necessitates proper infrastructure, which can be resource-intensive.
- Initial Setup and Cost: While the platform offers significant long-term benefits, the initial setup costs (sensor deployment, system integration, AI model customization) can be high, particularly for large-scale implementations.
- Connectivity challenges encountered in this case study:
  - Network Latency: Delays in real-time data streaming reduce the effectiveness of time-sensitive applications.
  - Data Loss: Missing data points compromise the accuracy of AI models and predictive analytics.
  - Data Storage: Big storage is needed to collect the data.
  - General Connectivity Issues: Poor network performance and reliability issues affect overall system effectiveness.
  - Costs: The cost of creating a platform and buying sensors and testing.

7. Conclusions and Future Directions

The inclusion of AI and DT technology in facilities management for mega-facilities shows significant capabilities for streamlining operations, improving decision-making and cost-saving. By utilizing real-time data, predictive analytics and scenario-based simulation of the AI-DT solution can proactively respond to maintenance activities in buildings, which optimizes energy consumption while providing good asset management. According to findings, the AI-based DT platform integrates real-time IoT sensor data with BIM models and predictive analytics to give a complete view of mega-facilities for management. Figure 12 summarizes how the DT can be applied for any building; by integrating the BIM LOD 500 model, IoT, and AI, it provides facility managers with tools to manage real-time monitoring, predictive maintenance, and scenario-based decision-making, resulting in significant improvements in operational efficiency, energy optimization, and collaboration between stake-holders. The case studies shared in this research confirm the effectiveness of the platform in bringing drastic improvements when it comes to reducing maintenance costs, achieving energy savings, and maximizing equipment uptime, which is one sure-shot way that could be helpful for mega-facilities.

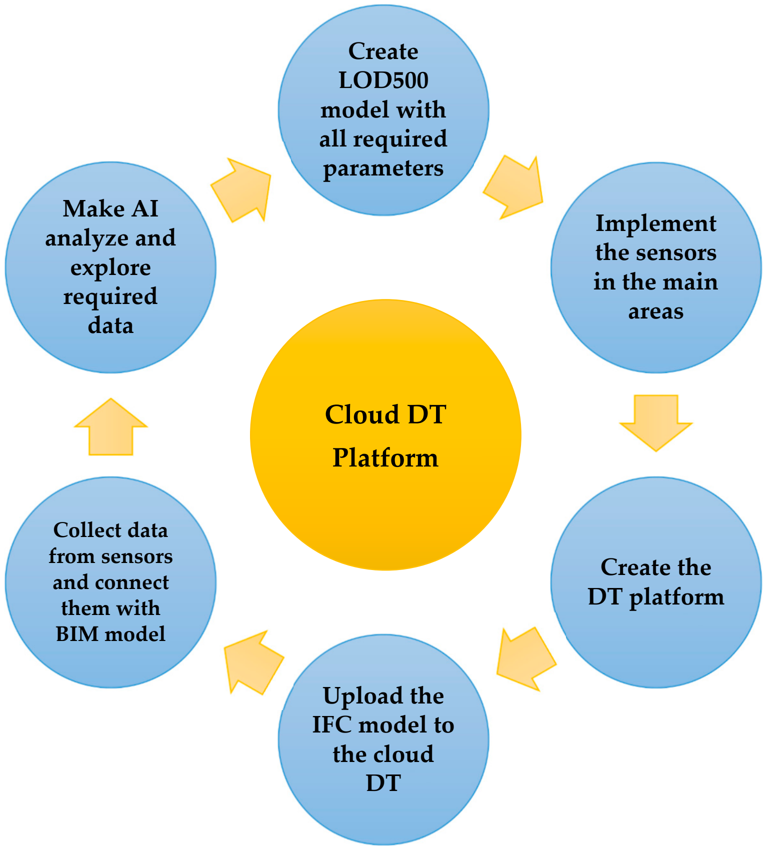

Figure 12. Framework for DT platform.

Data are not unified at an industrial scale, cybersecurity fears and big price tags to hook-up plant equipment with AI and DT gear: tackling these will be essential for releasing the full power of the technologies in FM. To achieve this, future studies are required to establish the data format standardizing process for sharing data securely over a network such as block chain technology and improve AI algorithms for real-time optimization. The future entails transformative potential with AI, DT, as well as up-and-coming technologies, including 5G and edge computing, converging to enable the creation of smart, self-learning structures that can adapt in real time based on situational changes. Moreover, it will be necessary to differentiate these frameworks with more expansive implementations of the technologies in smart city infrastructure and sustainable development.

Creating the required families of the equipment in the BIM by the vendors significantly accelerates the creation of models. Establishing a unified platform for vendors with all required parameters can help future projects and enhance the integration of DT technologies. Implementing subscription-based pricing platforms by all software mother companies will encourage more stakeholders to use the DT in their projects, which will impact directly maintenance and operation costs.

To apply a real case study, a huge investment is needed. Through addressing today's constraints, combined with moving forward with more creativity in practice and approaches, future practices can push AI and DT implementations to achieve a new standing level parallel, elevating their place by enabling mega-facility efficiency as a standard.

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Abbreviations

BIM	Building Information Modeling
BXP	BIM Execution Plan
IoT	Internet of Things
EIR	Employer's information requirement
DT	Digital Twin
AEC industry	Architecture, Engineering, and Construction industry
QA	Quality Assurance
QC	Quality Control
CDE	Common Data Environment
LOD	Level of Development
CCTV	Closed-circuit television

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