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Perspective

The Challenge of Machine Learning and Artificial Intelligence in the Construction Sector: The Lesson Learned from the Rome Technopole Project

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Abstract

Artificial Intelligence (AI) and Digital Twins (DTs) can support the digital and energy transition in the construction sector; however, their application to the built environment presents both opportunities and limitations. This study aims to give a critical perspective on the topic analyzing the related key challenges, including error assessment, model interpretability, data availability, cybersecurity risks, organizational constraints, and lifecycle costs. Where AI is nowadays developed as a context-dependent tool set, it is most effective when embedded within integrated socio-technical systems rather than adopted as a universal solution. Instead, DTs can be intended as an enabling framework, integrating AI, Internet of Things (IoT), Big Data, and Building Management Systems (BMS) to enhance energy performance, indoor environmental quality, safety, maintenance, and decision-making at both building and urban scales. The direction international research on these topics is facing is clear as evidenced by the wide number of research papers published. The future of these technologies moves towards a simulative approach oriented towards the sustainable and fair development goals and will bring a broad transformation of the building environment where they are ever more integrated into each social and technical aspect. The work is supported by a case study developed at Sapienza University of Rome founded by the Italian National Recovery and Resilience Plan within Flagship Project 2 (FP2), "Energy Transition and Digital Transition in Urban Regeneration and Construction," of the Rome Technopole ecosystem.

Keywords: Artificial Intelligence; Digital Twin; built environment; Rome technopole; sustainable development

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1. Introduction

We are currently experiencing a historical phase characterized by profound transformations and emerging challenges. Artificial Intelligence (AI) has begun to reshape most existing production processes. The construction sector, traditionally cautious toward innovation, has only recently started to embrace new technologies. The adoption of Building Information Modelling (BIM) has served as a bridge toward new digital paradigms, capable of reducing costs and complexity while providing valuable tools for all stakeholders across the construction value chain, including end users. The key drivers of Construction 4.0 are digital technologies and their synergistic interactions. The growing application of tools such as Artificial Intelligence, Machine Learning (ML), semantic and generative technologies, Big Data analytics, Blockchain, Digital Twin (DT), the Internet of Things (IoT), and cloud computing is increasingly playing a pivotal role in transforming the construction industry [1,2]. In parallel with the emergence of the Fifth Industrial Revolution, the concept of Construction 5.0 is now entering academic and professional discourse. Its fundamental principles emphasize information transparency, the integration of the human dimension within process chains, the decentralization of decision-making, the establishment of seamless data flows, and the promotion of automation, interconnection, and technological interoperability [3,4]. It is therefore essential to develop innovative digital systems for the management, monitoring, and simulation of infrastructures—systems capable of generating positive social and economic impacts; enhancing awareness of energy and safety issues; and providing users with effective operational tools. The quality of design within the public sector is defined by its dual mission: serving as a catalyst for wider processes of urban regeneration in social, environmental, economic, and cultural dimensions while remaining responsive to the needs of citizens and communities through attentive interpretation and informed action [3,4].

The COVID-19 pandemic has highlighted the need to adapt the current economic model towards greater environmental and social sustainability. By harnessing digital technologies, the EU wants to promote the development of renewable energy sources, optimize resource management and program a sustainable future. These elements are also underlined by the United Nations (UN) with the UNEP (United Nations Environmental Programme), which sets two fundamental lines for the 4th industrial revolution: "Digitalisation for sustainability", where proactive development and the use of digital tools to achieve environmental goals are emphasized, and "Sustainable digitalisation", which encourages the development of new technologies taking into account sustainability and environmental impact until the end of life [5,6]. The digital transition also entails significant challenges, including the need to ensure digital inclusion, safeguard data privacy and security, and address the ethical implications of emerging technologies. The sustainability requirements of processes and infrastructures are likewise central to the European Green Deal, introduced by the European Commission in June 2021, which commits Member States to achieving a 55% reduction in emissions by 2030 and climate neutrality by 2050 [7].

Answering the socio-economic crisis caused by the COVID-19 pandemic, the European Commission in May 2021 approved the National Recovery and Resilience Plan (also titled "Italia Domani"—Italy Tomorrow). The plan was approved in June 2021 under the NextGenerationEU initiative, defining a comprehensive policy framework designed to tackle the structural weaknesses in the Italian economy. It supports different initiatives, encouraging the development of research infrastructures and "living laboratories". In this framework, the Rome Technopole project was approved as a measure to improve the Latium region's (Italy) competitiveness, creating a collaborative environment where public and private stakeholders, both from knowledge and industrial sectors, are involved. The technopole aims toward advanced technologies and research in highly competitive sectors such as Energy Transition (EnT), Digital Transition (DgT), and Health and Biopharma (H&BP). Its headquarters will be built in the Pietralata district of Rome with the goal of representing the operational materialization of the Green City Approach on an urban scale [8–11]. This work emerges from the considerations developed during the activity developed for the Flagship Project 2 (FP2): "Energy Transition and Digital Transition in Urban Regeneration and Construction", where AI, ML, and digital technologies were investigated for use in the built environment.

To address these challenges, innovative tools oriented toward the digital transition are required. It is therefore essential to develop advanced digital systems for the management, monitoring, and simulation of infrastructures—systems capable of generating positive social and economic impacts; enhancing awareness of energy and safety issues; and providing users with effective operational tools. This article aims to outline this evolution, identify its limitations and potentialities, and offer a critical and contemporary interpretation. The research questions this paper aims to answer are:

- How can digital technologies improve building the environment?
- Simulations or AI, which is better and where do the two technologies differ?
- What are the limitations and challenges associated with AI for the built environment?
- What are the main discussed and researched topics related to AI for the built environment?
- What is the relationship between AI and DT for the future built environment?
- What is the lesson learned from an operative context using AI and DT?
- What is the expected direction of future development for AI in the built environment?

2. The Era of the Smart Environment

The fundamental principles of the Smart Environment are [12,13]:

- The human dimension of processes and their chain of transmission;
- Transparency of information;
- The decentralization of decision-making processes;
- The ability to have seamless data flows;
- Automation;
- Interconnection;
- Interoperability between technologies.

These principles can improve the anticipatory capacity of the project which, with the support of new AI technologies, can be much better able to give answers to the two categories of considerations. The first category relates to the approaches of contemporary design (on which the very sense of "Quality of Design" depends) and consists of:

1. Multiscale approach: The need to decentralize decision-making processes and enable seamless data flows with a wider vision [14–16].
2. Interdisciplinary approach: the progress from multidisciplinary to interdisciplinary collaboration [17,18].
3. Participatory approach: The need to develop effective communication among different stakeholders (as an example: public administrations, partners, designers, builders, and manufacturers) where the essential principles are information transparency, interconnection, and technological interoperability [19,20].
4. Programmatic approach: To promote a strong integration across the four main phases of the building process. It relies on data-driven and contextual knowledge, drawing on Big Data [21,22], sensor and Building Management System (BMS) data [23,24], digital surveys [25–27], and simulation-based predictive tools. During the project design phase, from conceptualization to execution, Building Information Modelling plays a central role, together with AI [9,28,29], IoT [9,28,29], semantic and generative technologies [9,28,29], and cloud computing [30–34]; third, the project for the construction and management of the construction site [35–37]. The approach also encompasses construction-site planning and management, as well as lifecycle strategies for operation, maintenance, and monitoring. In the latter phase, user participation and the human dimension are essential, alongside Smart Environment technologies and the synergistic interaction between humans and digital systems [8,38,39].

The second category relates to the specific "Quality" objectives of the project phase which pertain to six dimensions supported by the world of the Smart Environment:

1. Predictive dimension: The ability to predict the performance of proposed interventions with respect to objectives of environmental, social, and cultural sustainability; safety; seismic vulnerability mitigation; as well as the management of flows and service quality control [40–42]. These include energy transition modelling [43–45], climate change impact and adaptation forecasting [46–48], circular resource and waste management analysis [43–45], environmental quality assessment, and the spatial evaluation of green areas and ecosystem services [49–51]. The framework also incorporates social sustainability [7,8] and the protection and enhancement of cultural heritage, both tangible and intangible [52–54].
2. Temporal dimension: The capacity to correctly consider time, ensuring adherence to schedules while preserving the environmental value over time [55–57].
3. Cost dimension: The ability to include costs is no longer limited to the conventional economic considerations ("prices" and "quantities") but expanded into a holistic understanding of "cost," which also encompasses degradation costs, environmental costs, and social costs. This broader cost concept reflects the full range of impacts—beyond direct financial outlays—associated with an intervention across its lifecycle [58–60].
4. Mobility dimension: The capability to simulate and predict the fluxes around and inside buildings, evaluating people's movements, as well as urban contexts, the communities inhabiting them, and the transversal flows [61–63].
5. Spatial dimension: The capacity to simulate the renewed spatial and aesthetic dimensions envisioned by the project through the opportunities offered by mixed, augmented, and virtual reality technologies [64–68].
6. Sustainability dimension: The capacity to systematically integrate sustainability protocols and indicators into the design process is fundamental. Due to the growing complexity of interactions among design parameters and the multiple factors affecting how these protocols and indicators are applied, emerging digital, simulation, and computational technologies play—and will continue to play—a decisive role. Within this framework, the renewed alliance between enabling technological systems and the human dimension remains central to the effective implementation of such tools [3,4].

3. Key Concepts of Artificial Intelligence

AI constitutes the branch of knowledge dedicated to enabling machines to perceive their environment and execute actions guided by intelligence. The term "AI" is applicable to a broad field of algorithms able to perform tasks that typically require human intelligence, such as reasoning, understanding language, and problem-solving [69]. ML is a subfield of AI that encompasses computational techniques for data analysis and learning, relying on statistical processing that is inherently susceptible to errors and limitations arising from the dataset employed, underlying assumptions, technological constraints, and data volume [70]. While AI aims at general intelligent behaviour, ML emphasizes data-driven optimization and pattern recognition, making it more specialized. Deep Learning (DL), a further subset of ML, uses multi-layered neural networks to process complex data like images and text with high accuracy. It can become highly intricate, often obscuring interpretability across processing stages [71]. Lastly, generative AI is a subclass of AI designed to produce new, original content—such as text, images, audio, video, or code—based on patterns learned from vast training datasets (usually the internet), often in response to user prompts [72]. Instead, Computer Vision (CV) focuses on image analysis and information extraction therefrom [73]. Contemporary 3D space reconstruction has seen the emergence of Gaussian Splatting techniques improved by Deep Learning-based algorithms whose limitations stem from the noise it generates, yielding models that are frequently imprecise in dimensional accuracy [74,75].

However, each of these knowledge fields is different in terms of the application to the algorithms, accuracy and performance. The proper relationship between them is shown in the Venn diagram in Figure 1.

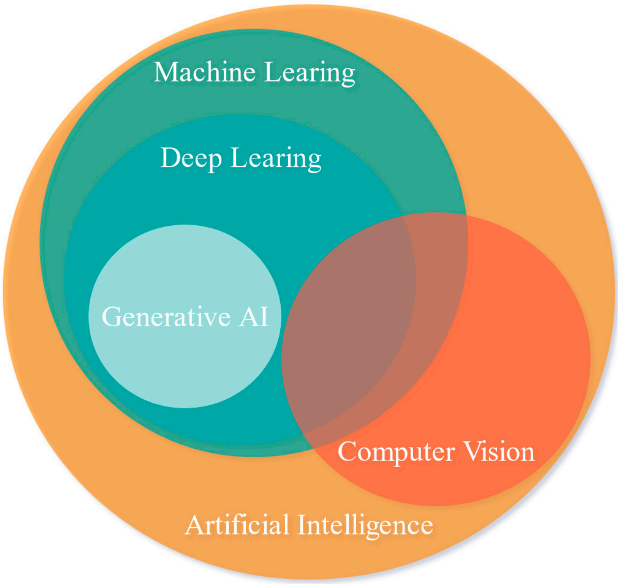

Figure 1. Hierarchical relationship between AI, ML, DL, CV and generative AI.

4. Trade-Offs of AI

Nowadays, AI represents a young yet rapidly evolving field of science. As such, it poses a range of issues that have not been fully explored and are currently the subject of extensive discussion and analysis within the international scientific community. Some of the most critical aspects in this regard are outlined below.

4.1. AI Errors Evaluation

The interpretation of errors generated by an AI algorithm is inherently more complex than that of the physical models or correlations typically employed in traditional forecasting. Although error is a quantifiable measure, its assessment must consider additional factors related to the model's quality and applicability. Common evaluation metrics include the confusion matrix, accuracy, precision, recall, and F1 score, as illustrated in Figure 2. These indicators are generally reported in model assessments to clarify the specific advantages and limitations of each model in processing and interpreting the analyzed data [76–78].

For instance, when evaluating the presence of a tumour through image analysis, it is preferable to employ a model that minimizes false negatives, even at the expense of a higher number of false positives, thereby allowing the actual outcome to be verified a posteriori through expert assessment [79,80]. The same principle applies to construction contexts in which safety constitutes a critical parameter. For instance, in the case of a hydrogen system monitored through a Fault Detection and Diagnostics (FDD) model, it is preferable to register additional false fault detections—prompting extraordinary inspections—rather than risk overlooking a potentially hazardous leak [81–83]. This concept is also true for simpler tasks, such as checking that an operator is really wearing PPE (Personal Protective Equipment) [84,85]. The selection of the most appropriate models thus depends on their specific field of application and the type of performance required. This issue is particularly relevant in domains where sufficient prior knowledge of model behaviour within the given context is lacking—such as the construction sector, which has only recently begun to address these challenges [86]. While it is possible to discuss the validation of an AI algorithm, this validation remains constrained by the complexity of error representation and is meaningful only when the available data are consistent with the intended application domain.

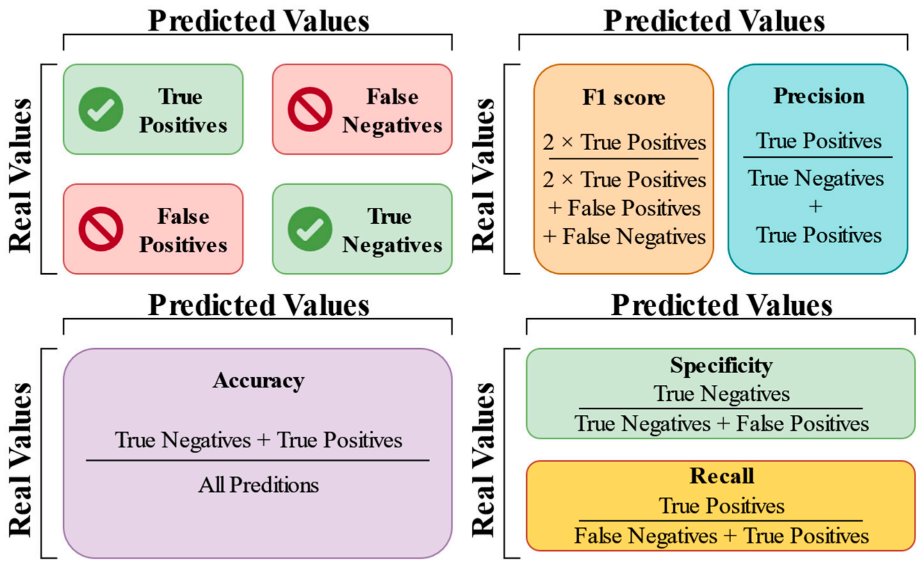

Figure 2. Examples of error evaluation metrics used in Machine Learning.

4.2. AI Trusting

Artificial Intelligence (AI) was originally conceived to provide answers based on experience, that is, on training data, without necessarily explaining the rationale behind its decisions. This limitation has become the focus of extensive research, leading to significant efforts in the development of interpretable neural networks and interpretability algorithms capable of elucidating cause–effect relationships [87–91]. For instance, if a building exhibits high energy consumption, understanding the underlying causes becomes essential for effective analysis and intervention. By using Deep Learning (DL) algorithms, it is possible to identify and characterize the problem; however, the underlying causes often remain insufficiently transparent and must typically be investigated by the user [92,93]. Any ML models are considered simpler than DL algorithms; for such models the relationship between input and output data is often transparent—as in the case of regression models or Decision Tree classifiers—thus ensuring data interpretability [91]. Likewise, physical or parametric models frequently establish direct correlations between inputs and outputs, offering a high level of transparency regarding the rationale underlying a given outcome. An illustrative example of this process, drawn from computer vision (CV) image classification algorithms for its clarity of representation, is presented in Figure 3 [94]. It becomes evident that only a portion of the image determines the algorithm's output selection. Non-interpretable models are commonly referred to as "black boxes," whereas interpretable models are described as "white boxes." Generally, a trade-off exists between interpretability and accuracy, with higher interpretability often associated with reduced predictive precision [95].

Data interpretability is also closely linked to the issue of trust; interpretable and well-justified data foster the virtuous and confident use of technology. Although training a neural network on physical correlations is theoretically possible, it is generally discouraged, as the errors inherent in the physical model would compound those of the ML algorithm [86]. This issue becomes particularly critical in the analysis of rare events (such as structural collapses or critical system failures), where data scarcity undermines confidence in model outputs [96–98]. The data problem is therefore dual in nature: on one hand, it is essential to ensure data security and controlled sharing; on the other, the development of reliable models requires extensive and well-structured datasets. These two aspects are discussed in the following sections.

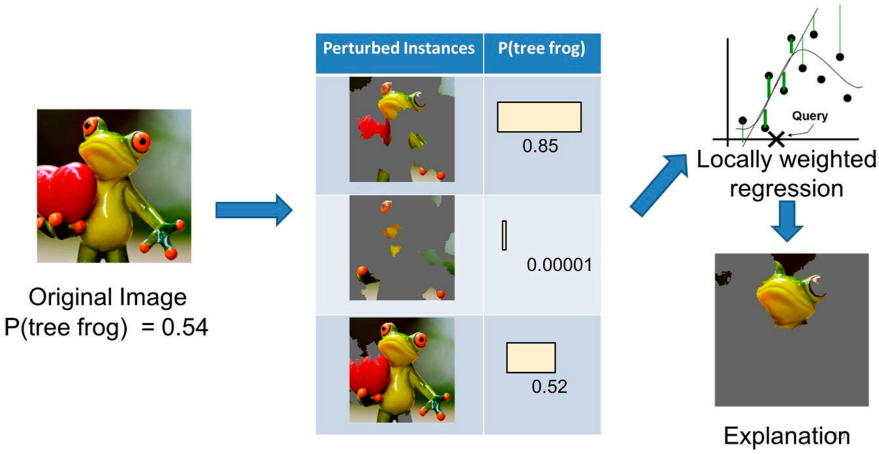

Figure 3. Representation of the decision-making process of an image classification algorithm: the evaluation that it is a frog with an accuracy of 54% depends predominantly on whether the model has found the frog's head; the same segmented image without a head provides a negative result; and the head alone provides an accuracy value of 85% [94].

4.3. AI Data Hunger

Despite the recent advancement in the field, currently there is no definitive answer about the amount of data required to train an AI algorithm [99]. As a general reference, for real-time CV image recognition networks, the YOLO (You Only Look Once) architecture requires approximately 1000 images to achieve acceptable results with an accuracy of around 60%. However, it is important to note that this performance is achieved using a model pre-trained on the open-source COCO database, which contains approximately 328,000 images [100,101]. In contrast, simpler algorithms of a purely numerical nature (involving few input and output variables) may require as few as 10,000 data points. Conversely, natural language processing networks (generative AI) capable of direct user interaction may require millions or even billions of data records, particularly in cases when the model needs to be pre-trained [102,103]. It must be noted that while model performance tends to improve as the number of samples increases, the rate of improvement progressively diminishes; beyond a certain threshold, the quality of data becomes more critical than its sheer volume [104].

This relationship underscores the intrinsic link between AI and Big Data, as managing vast datasets requires specialized technologies. Big Data systems must ensure timely access to any stored information, with "scalability" being a central concept—namely, the capacity to accommodate increases in database size over time without compromising performance. Scalability is a prerequisite for all expanding digital systems and should be incorporated at the design stage, rather than addressed retrospectively (unless a complete re-engineering process is intended) [105,106]. The challenge is even more pronounced in the case of AI models requiring direct access to documents or cloud-based documentation, such as Retrieval-Augmented Generation (RAG) systems [107]. These are highly effective for rapid data retrieval but depend on well-structured and organized datasets. Numerous reviews highlight that AI models rely on large, labelled datasets; however, in the construction, infrastructure, and site management sectors, data are often scarce, fragmented, noisy, or proprietary—hindering the training of robust, transferable models applicable across projects and geographical contexts [108–113]. Additionally, challenges related to overfitting and underfitting persist. Underfitting occurs when limited data fail to capture the complexity of the model, leading to overly generalized outputs, while overfitting arises when excessive training data causes the model to perform accurately only within its specific dataset [114]. This concept is illustrated in Figure 4.

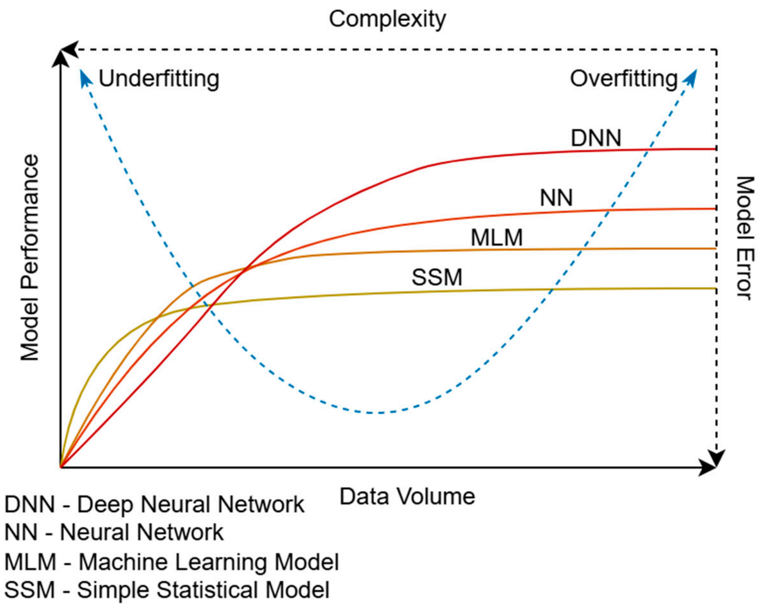

Figure 4. Qualitative representation of the relationship between error, complexity, performance and volume of training data. The more a model is trained on a high volume, the more specific it is and the gains in performance are reduced.

Modern AI models have the capability to self-learn and adjust their predictions based on real-time data acquisition [115–117]. However, this process is subject to several limitations. In cases where inefficiencies or anomalies arise from unidentifiable data—for instance, "drifts" caused by external phenomena that cannot be automatically detected—all control parameters, including predictive outputs, may be affected [118]. Such circumstances would necessitate retraining the model from the beginning. Moreover, since AI relies on statistical methods, the data used for training must be real rather than simulated; otherwise, the resulting predictions will be unreliable. Assumptions concerning data must also correspond to the intended application: for example, in estimating annual electricity consumption, data must be collected over an entire year to ensure valid outcomes [119]. When AI models are employed in place of previously validated physical models, inconsistencies in data relevance may further compromise accuracy. Consequently, model error verification must be conducted critically, considering all potential application domains, clearly defining the model's operational boundaries, and entrusting its evaluation to qualified experts rather than general users who may lack the necessary analytical tools to interpret results appropriately. Furthermore, data alone hold no intrinsic value unless they are collected, organized, structured, and expressed with clarity and precision. Assembling heterogeneous data without an underlying rationale does not yield meaningful insights; instead, it risks consuming storage capacity and introducing unnecessary complexity into the models, which must then process excessive or irrelevant information.

Data workflows should therefore be guided by clearly defined objectives rather than by the incidental availability of data. Additionally, because raw data are often prone to errors and inconsistencies, appropriate pre-processing is essential—AI models should never operate directly on unrefined datasets [120].

4.4. The Partnership Between IoT and AI

The terms Big Data and ML are frequently associated with the concept of the Internet of Things (IoT). The IoT refers to the network of devices connected to the internet, typically characterized by low cost and compact size—often classified as Commercial Off-The-Shelf (CotS) technologies [121,122]. In reality, data generated by IoT devices constitute only one potential source of information; these must be complemented by data from additional databases, including internal systems (such as BIM, management platforms, human resources records, administrative documentation, and scheduling systems) as well as external sources (such as meteorological, traffic, and satellite datasets) [123–125]. A common challenge lies in the fact that the data collected are often unstructured, heterogeneous, incomplete, or of low quality—sometimes even erroneous [126,127]. Nonetheless, the proliferation of IoT technologies offers a valuable and widespread source of data at a granular level, making their use essential for applications within the built environment. Despite this potential, several limitations continue to constrain their effective implementation:

1. If devices are connected to the network, they can lead to IT vulnerabilities and inadvertent exposure of sensitive data. The risk can also be physical if actions are carried out (e.g., locking staff inside a room).
2. IoT devices are typically composed of low-cost hardware and are primarily designed for low-risk home automation applications. However, when deployed in strategic or high-security environments, such devices may fail to meet the required performance standards or lack the necessary security certifications.
3. The IoT technology ecosystem comprises a wide range of vendors, with solutions often relying on distinct network protocols that are not inherently interoperable. Consequently, it becomes necessary to process and harmonize data through the adoption of middleware solutions aimed at integrating diverse technological standards. Dependence on a single supplier, however, may pose significant risks, particularly in the event of vendor failure or technological obsolescence.
4. Commercial IoT devices tend to be poorly configurable; data must be filtered and processed before being used within AI applications.
5. An excessive number of devices does not necessarily translate into higher data quality but rather increases the likelihood of system failures and management complexity. Devices should therefore be deployed judiciously, ensuring their use only where functionally necessary to avoid unnecessary redundancies and minimize maintenance demands. Furthermore, reliance on wireless networks may lead to bandwidth saturation, potentially causing interference or disruption to higher-priority services.
6. IoT devices tend to have a short technological lifespan, as rapid advancements in the field can quickly make existing systems obsolete. Failure to design solutions that are adaptable or upgradable may therefore lead to the premature abandonment of a given technology.
7. IoT devices require energy and regular maintenance, contributing to environmental impact and potentially generating electronic waste within their short lifecycle. This issue is further exacerbated in devices powered by non-rechargeable batteries.

To avoid unnecessary costs and additional management complexity, it is essential to assess the benefits associated with both the application and the density of IoT device installation. For instance, installing a smart plug for an office computer that is used only once a week due to remote working practices may fail to offset its economic and environmental costs within its useful lifespan. Conversely, employing a presence sensor capable of monitoring an entire space, combined with a single switchboard power metre, can generate significantly greater benefits at lower costs by enabling integrated control of multiple systems (e.g., lighting, air conditioning, and electrical utilities) [91]. A comparable issue arose with automatic lighting systems, whose advantages were found to be most evident inside service areas (such as warehouses and restrooms) or in spaces lacking timer controls [128,129]. It is estimated that nearly 20 billion IoT devices are currently connected worldwide (Figure 5); therefore, their cumulative energy consumption and environmental impact must not be underestimated [130]. It should be noted, however, that the usage of these devices extends well beyond the built environment, encompassing sectors such as automotive, industry, healthcare, and agriculture.

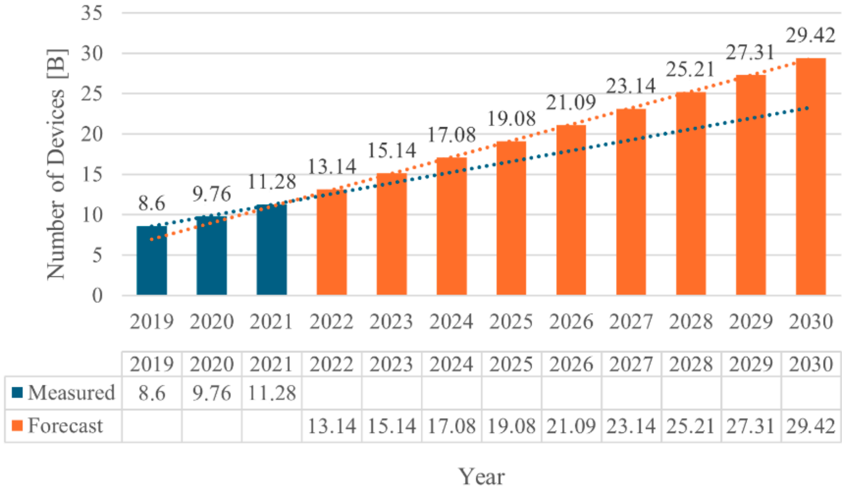

Figure 5. Forecast number of IoT-connected devices to 2030 [130]. Dotted lines are the quadratic interpolation for the measured and forecast data.

An optimal design strategy therefore requires the involvement of qualified experts, equipped with both technical training and the critical capacity to make informed decisions during the design of digital and physical architecture alike. Innovative BMS technologies enable interoperability with IoT systems, allowing the exploitation of existing data without incurring additional costs for the installation of new devices [131,132]. This process, however, inherently entails security risks and thus demands a high level of both digital and physical protection and reliability. In such contexts, the concept of interoperability between devices, systems, and data storage architecture becomes essential. Within the broader vision of Smart City development, where system scalability is a key prerequisite, the integration of IoT technologies is indispensable. Interoperability, therefore, emerges as a fundamental value, enabling the transferability and scalability of solutions across comparable contexts, ultimately contributing to the conceptual framework of a future "Smart Europe." [133].

4.5. Cybersecurity Aspects

A central and overarching theme connecting AI, IoT, and Big Data is the security of data and information. Every digital security system is inherently vulnerable, and the only theoretically secure computer is one that is fully isolated, disconnected from the internet and inaccessible to personnel. Since such a system would be functionally impractical, the most effective strategy involves minimizing critical exposure points (e.g., access nodes and wireless networks), regularly updating systems with security patches, and ensuring continuous maintenance [134,135]. As with a high-performance racing car, the more advanced and complex a system is, the greater the resources required to maintain its safety and operability. The ISO/IEC 27000 series defines the main standards for authentication and information security management, while AES 128-bit and 256-bit encryption are generally considered sufficiently secure for most applications [136–139]. However, minimizing cybersecurity risk also entails adopting preventive organizational measures such as avoiding unnecessary storage of sensitive data, limiting external interference within operational environments (as the presence of unauthorized individuals always constitutes a vulnerability), maintaining an up-to-date IT infrastructure, and providing continual cybersecurity training for all personnel [140–142]. It only takes a single weak component to compromise an entire system, as evidenced by the recent cyberattacks linked to the conflict in Ukraine [143]. Cybersecurity thus represents one of the most critical issues in the digital transition, with most incidents attributable to inadequate staff training or outdated technological infrastructures. A successful cyberattack can produce severe economic and social consequences, particularly when public infrastructures are affected.

Technologies such as Blockchain are not easily integrated within BMS and frameworks, as they lack sufficient update speed and entail significant energy consumption costs for each operation [144]. These limitations stem from the block validation process and network synchronization requirements, which render such systems suitable primarily for non-real-time or near-real-time applications. For example, Bitcoin requires approximately ten minutes to verify and distribute a new block, with each operation consuming the equivalent of up to 16,000 L of water, roughly 6.2 million times more than a single credit card transaction [119]. Consequently, Blockchain can only be employed as a security mechanism for slow transmission processes, where it nonetheless offers limited protection, as its security decreases inversely with the number of nodes connected to the network. Quantum cryptography, by contrast, remains an emerging technology that is not yet sufficiently mature for large-scale applications [145]. Its deployment is still constrained by high costs, particularly when compared to the modest requirements of individual networked devices such as smart plugs. Therefore, at present, traditional information security systems continue to represent the most effective solution in terms of cost–benefit performance.

The obligation to ensure cybersecurity also extends to the processing of personal data, as defined by the General Data Protection Regulation (GDPR) No. 2016/679 of the European Parliament and of the Council concerning the protection of natural people with regard to the processing and free movement of personal data, which repealed Directive 95/46/EC [146]. Additionally, Directive 2002/58/EC establishes the principles governing privacy and electronic communications in the telecommunications sector [147], while Directive (EU) 2016/1148 sets out measures to achieve a common level of network and information system security within the Union [148]. Finally, Regulation (EU) 2018/1807 introduces the legal framework for ensuring the free flow of non-personal data across the European Union [149].

4.6. Users' Training

The use of AI systems necessitates the presence of trained and informed operators who are capable of critically interpreting data and providing meaningful feedback to obtain useful insights and outputs. While anyone can interact with a generative AI system (such as ChatGPT GPT-5.5 Instant or Google Gemini 3), not all users possess the expertise required to evaluate the quality of the output. For instance, in the scientific community, hypotheses, results, and theses are substantiated through a state-of-the-art review grounded in citations from reputable international sources. However, many authors fail to recognize that generative models may fabricate citations that, while plausible in appearance, are entirely fictitious [150,151]. Furthermore, the proliferation of AI-generated academic papers—in some cases produced solely to enhance academic credentials rather than contribute genuine scientific value—raises serious concerns regarding the quality and integrity of scholarly discourse [152,153].

While the production of erroneous academic content might entail limited harm in certain contexts, inaccuracies become significantly more consequential when they pertain to fields such as energy analysis or environmental sustainability, where misinformation can directly affect economic outcomes and public health. When employing more complex AI algorithms, particularly those yielding numerical or analytical results, users may risk placing excessive confidence in outputs or failing to ensure the validity of input data and model assumptions [154,155]. AI systems are also susceptible to "hallucinations" or misclassifications, as exemplified in Figure 6, where an image recognition algorithm mistakenly identifies a dog as a tiger.

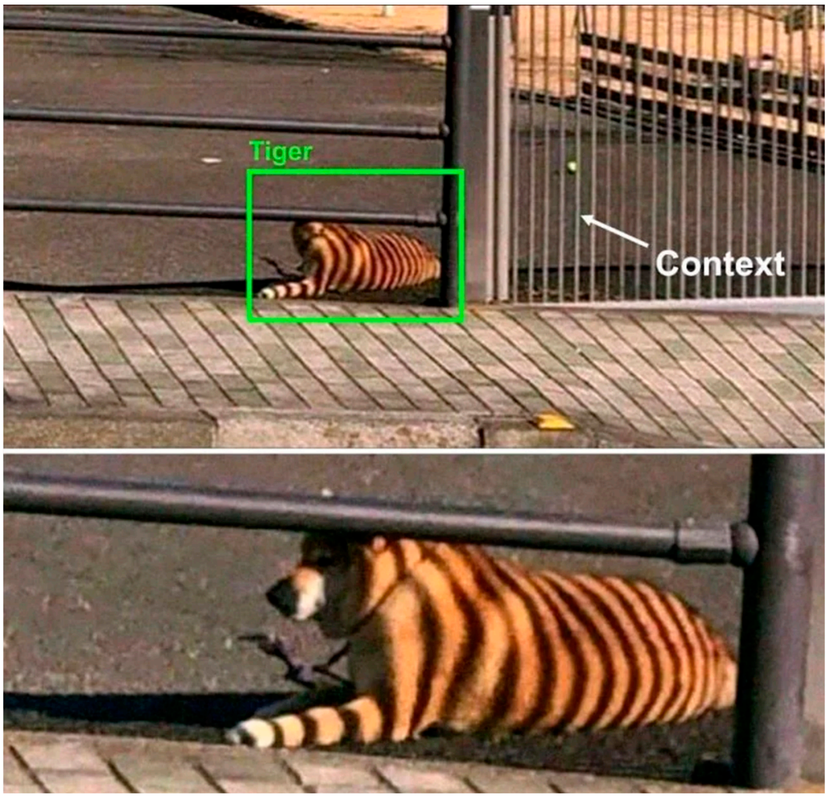

Figure 6. An example of AI hallucination where a common dog sitting under a fence shadow is recognized as a Bengal tiger (source: Reddit).

To mitigate these issues, it is essential to train experts capable of processing data and validating results, even when working with highly interpretable algorithms. Drawing on the Rasmussen model—originally developed for nuclear safety—it is crucial that operators undergo continuous training and change in duties to prevent errors arising from overconfidence or from underestimating the complexity of assigned tasks [156]. Given the frequent evolution of both models and platforms, it is currently untenable to assign unqualified personnel to highly specialized and sensitive operations [157,158]. Training should therefore be regarded as a strategic investment that yields long-term benefits. This challenge extends to the broader IoT and Big Data domains, where a significant shortage of qualified professionals remains a critical limitation.

4.7. AI Costs

The use of AI involves a high environmental and energy cost. Beyond the energy consumption associated with running algorithms in local data centres or cloud infrastructures, additional expenses arise from software licensing, personnel training, and specialized labour. For instance, the annual salary of a data scientist averages around USD 120,000, while a Machine Learning engineer earns approximately USD 160,000. Today, a single NVIDIA H200 GPU (NVIDIA Corporation, Santa Clara, CA, USA) processing unit for Machine Learning applications can cost up to USD 315,000. According to Statista, global spending on AI reached approximately USD 154 billion in 2023 [159].

However, the cost shall be assessed at the building scale for applications related to the built environment. When using on-premises licenses—i.e., locally hosted systems where all information remains within the internal network—annual costs for a comprehensive monitoring service based on a BAS typically range from approximately €30,000 to €150,000 for buildings between 1000 and 3000 m^2. For larger and more complex structures, or when additional functionality and redundancy are introduced, costs may reach up to €1 million [31]. As an alternative to commercial systems, open-source solutions may be adopted. Although these represent low-cost and non-proprietary options, they too present limitations, particularly due to the absence of technical support and the advanced knowledge required for their effective use [160,161]. Currently, there is no definitive consensus regarding cost efficiency between open-source and proprietary solutions [162,163]. Theoretically, an optimal configuration should emerge from a balanced and critical assessment of multiple parameters—including system complexity, algorithm selection, response time, number of devices, and redundancy—to identify the configuration that minimizes cost while maintaining reliable performance.

For instance, the computational power required by a DL algorithm may be up to 10,000 times greater than that of a simpler classifier that can still achieve acceptable accuracy [164]. It follows that the optimal configuration should be determined by minimizing the combined cost of potential system failures and overall system complexity, as illustrated in Figure 7. Such an assessment remains context-dependent and must be tailored to the specific application and intended objectives, precluding any generalized solution.

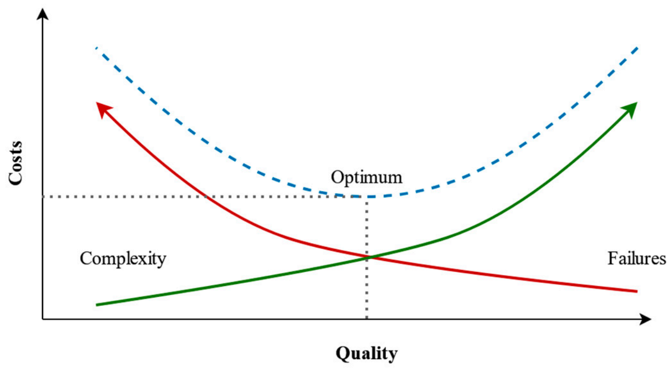

Figure 7. The relationship between the cost of complexity and failures. In the figure, the red line indicates the failure rate, the green line indicates the complexity of the product, and the dotted lines is the sum of complexity and failure rates where the minimum is the optimal value.

4.8. Organizational Difficulties

The adoption of new technologies inevitably raises social and organizational challenges that cut across both digital and energy transitions. A particularly significant obstacle lies in the resistance of employees to technological innovation. Much of the workforce demonstrates reluctance to learn new tools or alter established routines, as employees often feel comfortable and proficient within the framework of familiar technologies [165]. Concerns about the complexity of emerging systems can lead to rejection or skepticism, despite their potential advantages. Furthermore, apprehension regarding potential job displacement, stemming from limited digital literacy, may exacerbate this resistance [166]. Even at the managerial level, a lack of expertise in new digital technologies can result in a preference for established practices that require neither additional financial investment nor time for requalification [167].

Nonetheless, it is at the management level that the degree of technological adoption must be defined [168]. Leadership must ensure the allocation of appropriate resources, institutional sponsorship, and the formulation of a coherent implementation strategy. Equally important is the assessment of the organization's capacity to accommodate change. The effective integration of new technologies demands significant investment, the availability of qualified experts, and a careful evaluation of the associated Technology Readiness Level (TRL) to identify technological requirements [169]. In many cases, organizational models must be restructured to embrace innovation, a process that necessitates commitment, coordination, and engagement across the entire organization.

5. AI for the Construction Sector

The construction sector has increasingly begun to explore the potential of AI technologies. A review of international literature reveals a growing number of studies focused on the application of ML and DL techniques to areas such as energy efficiency, environmental quality, environmental impact assessment, material selection, and the automation of management, monitoring, and control processes [170–175]. According to data from the Mendeley database, nearly 2100 scientific review articles containing the keywords "AI" and "buildings" were published in 2025; when all articles—beyond reviews—are considered, the number exceeds 10,650. This clearly demonstrates the expanding scholarly and professional interest in the topic. Table 1 presents a synthesis of the most frequently addressed research themes, based on the thematic subdivision of the most discussed topics conducted by Gugliermetti et al. [38,91]. As can be seen from the results some topics are prevalent, such as environmental, energy and studies related to construction sites.

Table 1. List of the most discussed topics for AI in the built environment in the period 2017–2026 on the Mendeley database considering papers, reports, theses, books, and proceedings based on the thematic subdivision of the most discussed topics [38,91].

Main Category	Total	Percentage	Subcategory	Number	Percentage to Topic	Percentage to Total
Energy	8362	10%	Electricity	2529	30%	2.9%
			Thermal loads	3266	39%	3.8%
			Alternative energy carriers	2567	31%	2.9%
Environment	18,431	21%	Air quality	2397	13%	2.8%
			Noise	2536	14%	2.9%
			Temperature and humidity	4947	27%	5.7%
			Construction materials	5000	27%	5.7%
			Lighting	3551	19%	4.1%
Construction sites	15,891	18%	Processes and organization	3624	23%	4.2%
			Quality	3039	19%	3.5%
			Documentation	371	2%	0.4%
			Risks/Costs	4717	30%	5.4%
			Safety	4140	26%	4.8%
Water	5923	7%	Flows	3.595	61%	4.1%
			Rainwater	2.328	39%	2.7%
Green/gardens	3370	4%	Vegetation	3.370	-	3.9%

Table 1. *Cont.*

Main Category	Total	Percentage	Subcategory	Number	Percentage to Topic	Percentage to Total
Security	9509	11%	Physics/Digital	6.622	70%	7.6%
			Emergencies	2.887	30%	3.3%
Maintenance	4829	6%	FDD	2.579	53%	3.0%
			Interventions	2.250	47%	2.6%
Presence/activities	4690	5%	Activities and movements	1.988	42%	2.3%
			Presence	2.702	58%	3.1%
Waste/weeds	3108	4%	Wildlife	159	5%	0.2%
			Waste	2.949	95%	3.4%
Mobility	5632	6%	Parking/micromobility	180	3%	0.2%
			Transport/accidents	2.972	53%	3.4%
			Electric Vehicle Charging	2.480	44%	2.8%
Structural conditions	7340	8%	Building	7.340	-	8.4%
Total	**87,085**					

Digital Twins and AI

However, the application of AI algorithms remains largely confined to the evaluation of individual technical aspects within the specific contexts for which they are designed. The Digital Twin (DT) is the essential integrative component that enables the effective implementation and coordination of AI algorithms within the built environment. According to M. Grieves, who first introduced the concept, a DT is: *"A virtual representation of a physical object or system that spans its lifecycle and is updated from real-time data. It uses simulation, machine learning and reasoning to help make decisions" [176].*

In the context of the built environment, a DT system is the sum of all the software and hardware tools required for real-time and predictive monitoring and control of internal, external, and adjacent environments relative to the installation site. Where the first applications involved static 3D model representations of buildings [91,177], nowadays DTs are made of dynamic and animated representations of buildings since the first phases of the project [178,179]. The DT concept can be extended across multiple operational domains in which continuous environmental monitoring, data-driven learning, and autonomous decision-making are needed. From this perspective, the DT transcends the role of a mere virtual replica, evolving into a decision-making node that coordinates energy management, transportation, comfort, safety, maintenance, and structural integrity through automated data flows and learning algorithms [36,180–185]. Such functionality is achievable only through the integration of advanced AI techniques, allowing the system to extend beyond the building's immediate operational scope and serve as an interface with the surrounding district or, potentially, the entire urban fabric [25,41,186,187]. Moreover, recent reviews show how DTs can benefit from different digital technologies other than AI such as BIM [188,189], IoT [190,191] and GIS [192,193] to create multiscale, real-time models from single buildings to smart cities [194,195].

A conceptual Digital Twin architecture is reported in Figure 8 where the main key technologies are reported on the left, and on the right are reported the main functional components and capabilities.

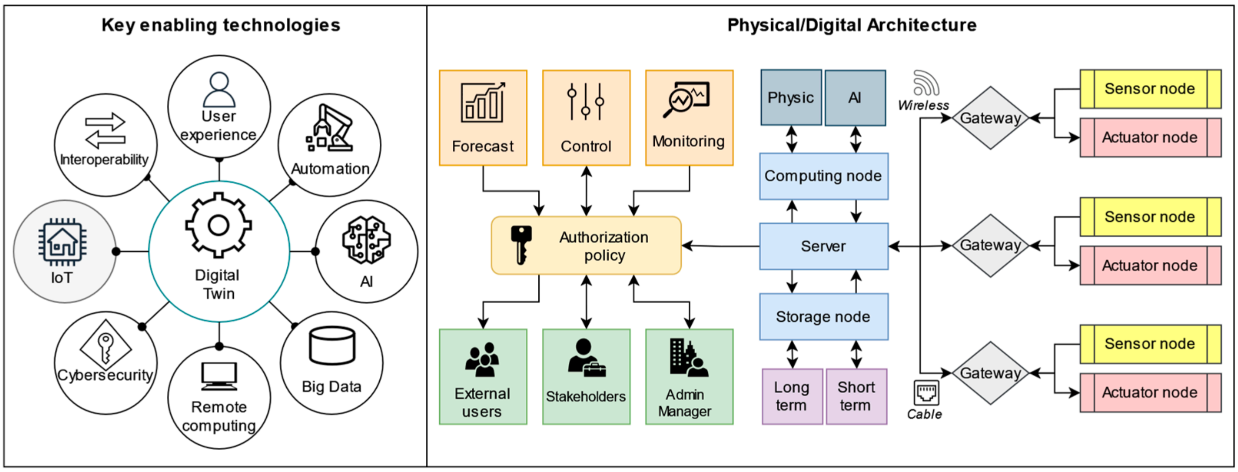

Figure 8. Conceptual Digital Twin architecture. In the left part of the figure colors indicates the same type of elements: Green for user type, orange for visualization components, light blue for computers, dark blue for algorithms, purple for databases, grey for communication gateways, yellow for IoT sensors and red for IoT actuators.

A DT must be capable of acting directly and autonomously upon the built environment by modifying the parameters that define its performance, for instance, by regulating lighting and air-conditioning systems, implementing real-time environmental monitoring strategies (such as estimating CO_2 emissions), or ensuring high levels of safety and efficiency through predictive structural analysis [185,196]. Frameworks now emphasize continuous sensor data, cloud platforms, and advanced analytics for monitoring, simulation, and control across the facility life cycle [185,197,198]. As an example of application, Lu et al. developed a DT-enabled Bayesian change point method to detect contextual anomalies in centrifugal pumps under varying loads, enabling continuous, automated monitoring in buildings [199]. Another example is reported in the work of Xie et al. where a Digital Twin data platform tags sensor streams with machine-readable fault labels and automatically selects informative sensors, reducing overfitting and computation while supporting dynamic asset management [200]. Hosseini Gourabpasi A. & Nik-Bakht M. developed the integration of automated analytics for BIM software which creates a facility Digital Twin that compensates for missing sensors by generating dynamic BIM features and supports model reuse across HVAC systems [201]. About the topic of predictive analytics and forecasting, Zhuang et al. developed a DT system capable of increasing HVAC energy savings by 17.4% and comfort in a surrogate by a coupled forecasting model by 16.9% [202]. Petri et al. created a four-layer, AI-driven DT for an industrial cold store that integrated semantic modelling, energy simulation, and optimization, achieving 15–18% energy cost savings, several thousand kWh of electricity savings, and over a ton of CO_2 emissions avoided while maintaining required temperature performance [203]. BIM-IoT data integration was investigated by Eneyew et al. who developed a BIM-IoT DT system for smart buildings using ontology-based query mediation, showing better performance and suitability for supporting real-time monitoring and predictive capabilities than an existing BIM-IoT integration approach [204]. Lastly, Geo et al. bridged DT by combining WebGIS, WebBIM, and graph algorithms within a three-layer architecture and a common data environment enables real-time monitoring, drone inspections, maintenance planning, traffic diversion, and logistics optimization, improving bridge operation and maintenance efficiency, safety, and decision-making [205]. As evidenced, there are many applications of Digital Twin for the built environment of which only a few are reported. DT systems can incorporate the complex network of relationships among the various entities that constitute a building—people, systems, and structural components—and be endowed with semantic intelligence. This would enable them to generate context-aware representations of building processes, expressed both textually and verbally through the application of AI and DL technologies.

6. The Case Study of the Rome Technopole

The considerations and perspectives discussed in this paper originate from the case study of the Energy and Environmental DT system developed at Sapienza University of Rome, within the Faculty of Architecture inside the interdepartmental research centre of CITERA (Interdepartmental Centre for Territory, Construction, Restoration, and Environment). The reference structure associated with this study is illustrated in Figure 9 [91]. The building under examination is a university facility that accommodates a research centre and, as such, encompasses three distinct functional areas: laboratories, administrative offices, and classrooms. The DT developed for the case study integrates AI technologies and IoT devices designed for application within the built environment. Notably, no automatic control actions are implemented without user feedback, as the improper activation of actuators could inadvertently result in undesirable events (such as deactivating lighting or power supply during scientific experiments or lectures).

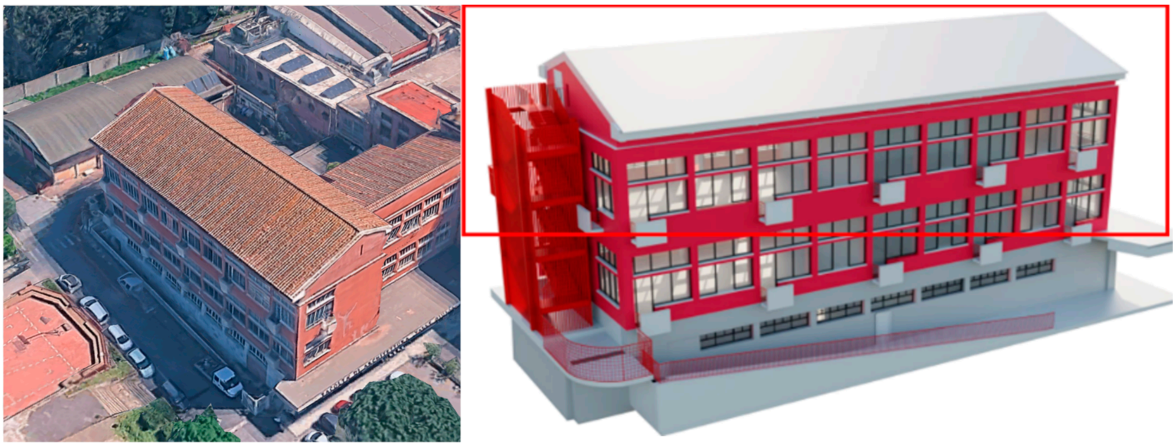

Figure 9. DT system developed for the CITERA (Interdepartmental Center for Territory, Construction, Restoration and Environment) at Sapienza University of Rome [91]. CITERA center is evidenced by the red box on the 3D BIM model on the left side of the figure.

Although such automated implementations are technically feasible, a human-in-the-loop approach was adopted to prevent potential disruptions, particularly given the experimental nature of the system and the involvement of students and doctoral researchers. The monitored parameters are reported in Table 2:

Table 2. List of the most parameters monitored by the DT system of CITERA [38,91].

Type of Parameter	Quantity	Unit
Electrical Parameters	Instantaneous power	W
	Average power	W
	Operational status	on/off
	Usage duration	min
	Time of operation	min
	Total energy consumption	kWh

Table 2. *Cont.*

Type of Parameter	Quantity	Unit
Indoor Environmental Parameters	Total Volatile Organic Compounds (tVOC)	ppm
	Particulate Matter ($PM_{2.5}$, PM_{10})	ppb
	Temperature	°C
	Relative humidity	%
	Carbon dioxide (CO_2) concentration	ppm
Comfort Parameters	Perceived temperature	°C
	Predicted Mean Vote (PMV)	-
	Predicted Percentage of Dissatisfied (PPD)	%
Occupancy Parameters	Presence or absence of occupants	-
External Environmental Parameters	Illuminance	lux
	Wind speed	m/s
	Wind direction	°
	Rainfall	mm/min
	Total rain	mm/m^2
	Solar radiation	W/m^2
	Ambient temperature	°C
	Radiative temperature	°C
	Outdoor relative humidity	%

The developed system is further designed to achieve the following objectives:

- Electricity monitoring and dynamic load forecasting, including the estimation of total annual energy consumption at the level of each individual connected workstation or device.
- Occupancy monitoring and space utilization forecasting to optimize the management of building areas.
- Monitoring and assessment of indoor air quality to ensure optimal comfort and health conditions for occupants.
- Monitoring of lighting comfort to enable the automatic adjustment of illumination levels in each room, thereby maintaining appropriate visibility and safety conditions.
- Monitoring and forecasting of thermal comfort to regulate air-conditioning systems and facilitate natural ventilation through the controlled opening of windows and doors.
- Verification of the interoperability of data transfer protocols and the adoption of widely recognized communication standards.
- Assessment of the feasibility of managing data within a dedicated on-premises infrastructure based on open-source technologies.
- Inspection and analysis of data using aggregated metrics and three-dimensional (3D) models.
- Implementation of an alert system designed to provide recommendations to facility managers in the event of system malfunctions or failures.

To ensure the use of safe and certified systems, CotS sensors and devices were adopted, thereby minimizing potential risks associated with their use. The configuration of the various systems and the distribution of sensor types across rooms are illustrated in Figure 10.

The symbols used in Figure 2 represent each type of sensor or actuator. The positioning illustrated is purely indicative, as the actual configuration depends on the feasibility of installing the sensors at the specified locations. Furthermore, the number of elements depicted in the figure denotes the presence of the devices rather than their exact quantity, as each workstation is equipped with a dedicated sensor.

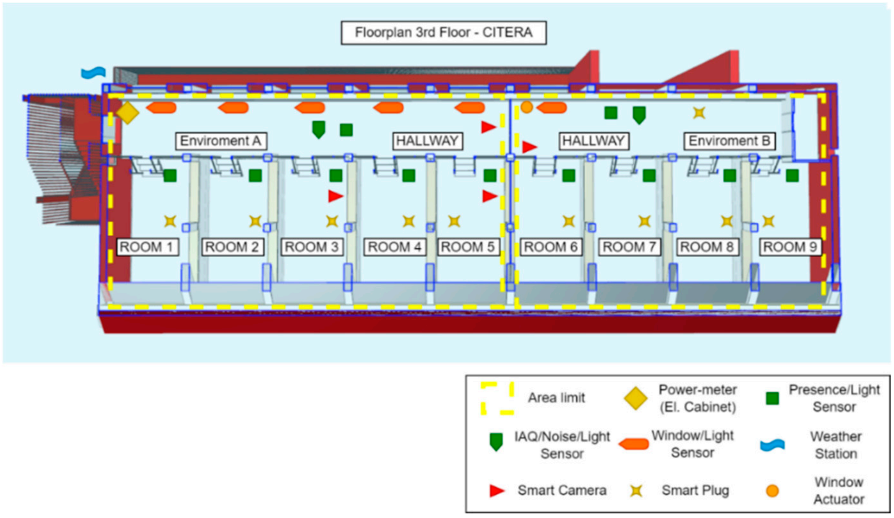

Figure 10. Layout of IoT sensors in the case study.

The operational architecture developed is reported in Figure 11 and it was designed based on the conceptual one reported in Figure 8. The figure contains all the details of the different operative technologies used in the case study as well as the logical connection between the components.

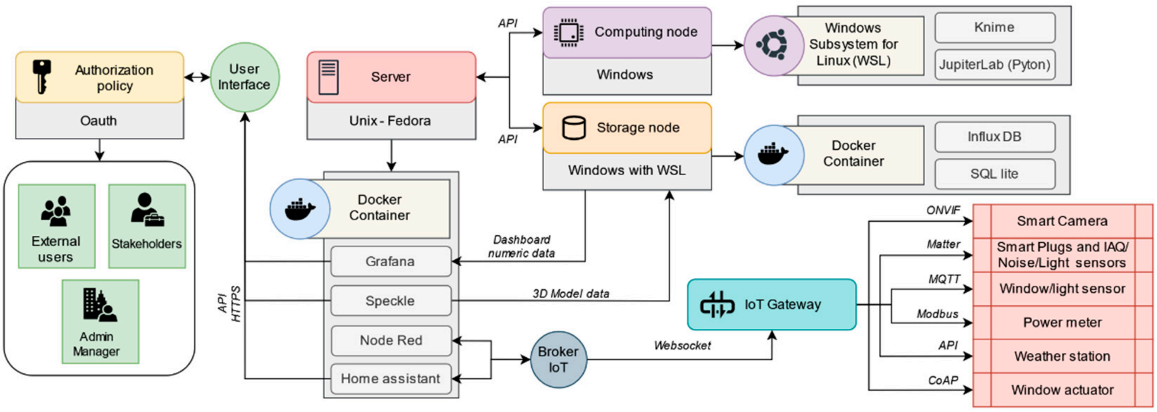

Figure 11. Operative Digital Twin Architecture developed for the CITERA research centre.

The details of the different components of the architecture are reported in the next sections.

6.1. Communication Protocols

Communication among the IoT hardware is allowed through a range of communication protocols. During the design phase, efforts were made to standardize, as far as possible, the types of data communication protocols employed. The preference was given to hardware from the same manufacturer—where feasible—and to devices equipped with open communication libraries already integrated into major existing DT platforms. Ensuring interoperability among different devices enables the minimization of data protocol variety, thereby promoting standardization in data packet formats and enhancing the exchangeability and compatibility of systems produced by different manufacturers [206,207]. The list of protocols implemented is reported below:

- HTTPS—used for establishing secure connections and data exchange with any device registered on the monitoring platform.
- API REST—employed for managing data requests over HTTPS via Application Programming Interfaces (APIs); this protocol supports communication between local and remote servers.
- CoAP—utilized for devices compliant with RFC 7252.
- Matter—adopted for general-purpose IoT devices. Developed by Google, this recent protocol enables standardized communication across smart home devices, aiming to unify sensor interoperability under a single communication framework.
- MQTT—a lightweight messaging protocol widely used in IoT networks for efficient, low-bandwidth data transmission.
- Modbus—implemented for communication with industrial-grade equipment, such as panel-mounted power meters.
- ONVIF—applied to manage video streaming and data exchange from IP cameras.

6.2. DT Interface and Platform

The selection of the platform was guided by the specific requirements of the building. Open-source platforms and software, which can be modified and integrated with custom components, represent the most appropriate choice for a research-oriented Digital Twin System (DTS). Software components are executed inside dedicated Docker containers to reduce workloads, isolate runtimes, reduce conflicts, and improve security. The authorization policies are organized using OAuth 2.0. Almost all services run on Unix-based operative systems, but due to constraints related to GPU drivers, the computing node runs under a Windows® environment using Windows Subsystem for Linux (WSL). The system user interface is shown in Figure 12:

Figure 12. Screenshot of the user graphical interface for the DT system developed at CITERA.

Based on the experience gained in this field and the current state of the art, the following technologies were selected [23,29,208]:

- Node-RED 3.1 is employed for automating data flows, performing complex variable calculations, and managing sensor-to-database event handling.

- Home Assistant version 2025.10.4 is used as a communication broker between the sensors and the data platform. The software enables the creation of user profiles with differentiated access permissions and provides a web-based interface that supports hardware from vendors across the IoT ecosystem.
- KNIME Data Analytics 5.8 LTS and Jupyter Lab 4.0 are integrated with Scikit-learn 1.7.2 and custom Python 3.13 libraries for executing AI algorithms, computing complex variables, and generating data-driven feedback loops.
- Data storage is structured in two layers: InfluxDB 2.0 is used for optimized long-term storage of time-series data, while SQLite 3.49.2 is employed for managing low-persistence data.
- Grafana 12.3.6 is implemented as a web-based interface for real-time data visualization and system monitoring.

6.3. AI Algorithms for Interpretable DT

To monitor all parameters and generate forecast estimates, the DT system has been integrated with AI algorithms capable of producing aggregated and interpretable metrics for users. The following list details the algorithms employed, based on analyses previously presented in an earlier scientific publication [91]. The technologies utilized are outlined below:

- Air quality forecasting is performed using Artificial Intelligence (AI) algorithms based on Gradient Boosting Regression (GBR) combined with SHapley Additive exPlanations (SHAP). The model functions both as a classifier—to predict air quality categories (poor, moderate, and good)—and as a regression algorithm to estimate anticipated quantitative values [209,210]. The input dataset is further enriched through the integration of data obtained from local meteorological services.
- Estimation of thermal loads and air-conditioning energy requirements is performed through a Support Vector Machine (SVM) model integrated with Local Interpretable Model-Agnostic Explanations (LIME) to evaluate the efficiency of air-conditioning systems based on physical data [92,211]. For thermal load estimation, an Artificial Neural Network (ANN) is employed, with the resulting outputs made interpretable through LIME [211,212]. The use of a neural network is justified by the variability in occupancy patterns and the opening of windows and doors, factors that are not easily captured by alternative models. By leveraging sensor data, the system enables the estimation of HVAC energy demands through an efficiency-oriented analytical framework.
- Solar radiation forecasting is performed by the external National Meteorological Service through an API interface. The acquired data are subsequently integrated and compared with measurements obtained from the local weather station. Owing to the complexity inherent in processing meteorological data, no dedicated algorithms were implemented; instead, the system relies on official weather forecasts as the primary source of predictive information.
- Occupancy forecasting is performed using a Generalized Additive Model (GAM) combined with SHapley Additive exPlanations (SHAP) [213,214]. Predicting the number of occupants within a given environment at a specific time is inherently complex, particularly in a research facility where presence and working hours are highly variable and not subject to fixed schedules. Nevertheless, occupancy is closely correlated with several key parameters—such as air quality, thermal comfort, energy consumption, and working time—making it one of the principal variables in the study. It should also be noted that occupancy data constitutes sensitive information from

a security standpoint, and access to such data must therefore be restricted and not publicly disclosed.
- The prediction of indoor thermal and visual comfort is performed using Generalized Additive Model (GAM) algorithms based on data from temperature and luminance sensors. User recommendations regarding window operation and the adjustment of air-conditioning setpoints are generated through Decision Tree models [215].
- Electrical load forecasting is performed using an ANN model integrated with LIME and incorporates occupancy forecasting as an input variable [216].
- Fault detection and load profiling are applied exclusively to electrical devices connected through smart plugs and are based on FDD algorithms for anomaly identification and simple Decision Tree models for load profiling [83].

The performance verification of the system is not included in this article, as data have not yet been collected over a sufficiently long period (at least one year) to evaluate the model's accuracy under all possible climatic and occupancy conditions. At present, the infrastructure has been operational for about 8 months.

7. Discussion on Future Perspectives for AI in Building Environment

The experience gained during the development and testing phases of the CITERA DT system has revealed a series of critical issues and reflections that form the basis of this study. The adoption of emerging technologies is undoubtedly associated with a range of benefits that may serve as key enablers of future sustainable development [217–219]. With specific regard to AI applications for the built environment, several strategic perspectives have been identified to promote their broader adoption while ensuring compliance with the ongoing digital, energy, and data protection transitions:
- Future developments in AI for the built environment should focus on automating and formalizing the logical pathways that underpin decision-making processes. This would enable the planning and scheduling of operational activities based on real-time data rather than manual or sequential information processing. Advanced AI systems should evolve toward autonomous decision generation, integrating large volumes of multisource data to support context-aware, adaptive management. Although current models can perform logical "reasoning" (iterative decision-making processes that assess multiple potential outcomes) further refinement is needed to tailor these capabilities to the specific complexity of built environment systems [220–223]. Greater automation can also reduce human error and shift low-value-added tasks to digital systems, thereby improving efficiency. Moreover, enhanced data-driven models could support predictive maintenance, optimize resource use, and ensure sustained performance and reliability across building networks.
- Future advancements should aim to enhance the computational efficiency of AI processes by minimizing the resource demands associated with their operation. Although automation enables the reduction in operational times, the continuous and predictive monitoring of system dynamics, and the optimization of building management costs, the implementation of AI systems remains resource-intensive. Their computational and energy costs increase proportionally with model complexity and data volume [222,224]. To ensure sustainable development, it is essential to employ lightweight, application-specific models dedicated to individual building functions, while reserving the use of general-purpose AI systems for high-level tasks where alternative solutions are not feasible.
- Another key perspective concerns the development of interpretable algorithms. The interpretability of AI models has become increasingly feasible through the emergence of dedicated methods designed to identify and explain the parameters that most

influence model outputs [88,225]. Without interpretability, many AI models lack transparency and reliability, making it difficult for operators to understand which factors should be adjusted to optimize performance, reduce operational costs, and enhance environmental and energy sustainability.

- Another important direction for improvement involves the development of "low-code" or "no-code" programming and development environments, which enable the creation and customization of AI systems without requiring advanced computational or programming expertise [226,227]. This need is particularly evident in non-technical academic disciplines, where students often lack programming skills and therefore encounter difficulties when working directly with low-level code. Similar challenges arise in many professional contexts, where employees are frequently not trained in the use or programming of such digital tools.
- Future developments should focus on developing models capable of managing assets at scale, enabling the dynamic expansion of infrastructure as needed [105,106]. In retrofitting projects, implementation often begins with a limited number of environments and is subsequently extended to larger areas; a similar scalable approach should be adopted for the deployment of AI and DT systems.
- It is essential to train personnel on the potential implications of AI, particularly concerning safety and risk prevention. AI applications can be employed to predict thermal and vibrational hazards or to assess the correct use of personal protective equipment [228,229]. Furthermore, such systems can support the localization, monitoring, and alerting of workers operating in hazardous, remote, or otherwise challenging environments [230]. AI technologies also enable the detection and monitoring of physical risks—such as fires, floods, or electrical faults—by providing real-time information that supports damage reduction and the formulation of effective intervention strategies [231,232].
- Achieving greater interoperability among different systems and technologies is a key challenge. At present, multiple hardware and software communication protocols coexist, often leading to fragmentation. In many cases, manufacturers seek to retain users within proprietary ecosystems by limiting external access to sensor-generated data. Only in recent years have genuinely interoperable technologies begun to emerge, fostering improved data exchange and system integration across different platforms [33,233].
- Expanding the use of open-source software is essential, as openness to the community represents a key criterion for evaluation—particularly for public administrations that seek to avoid dependence on a single supplier and require full transparency in data management and protection [161,163].

8. Conclusions

The adoption of AI constitutes a key factor in enhancing competitiveness and reducing operational costs, as it enables the creation of added value through the minimization of downtime and the delegation of repetitive or low-level tasks to automated systems. Product innovation facilitated by AI leads to the development of new services directed toward various stakeholders, including facility managers, public administrations, and citizens. Examples include automated service systems such as offices or platforms for monitoring administrative procedural status, both of which exemplify the potential of emerging technologies to transform service delivery. Enhancing sustainability remains a fundamental objective for future development. The integration of IoT, AI, and DT technologies can support the efficient allocation of critical resources such as water, energy, and raw materials. Furthermore, pollution monitoring enabled by these technologies allows for the formulation of strategies to reduce emissions, mitigate environmental impact, and promote healthier and safer working environments for both employees and communities. Another dimension of growing importance is user satisfaction—understood as the perception and evaluation expressed by users regarding services or algorithms that affect their domains of interest. AI systems can assist in identifying critical issues or negative feedback, thereby serving as essential instruments for improving service quality. Future developments may include the use of Deep Learning algorithms to detect inconsistencies or deficiencies in administrative documentation. The case study conducted at the Sapienza University of Rome has provided a basis for discussion and a hand-over of the technology, allowing the development of a series of critical considerations regarding the possibilities and limitations of these technologies, tracing a vision for their future development. The application potential in the construction and urban planning sector is evident as is the need to develop scalable, interoperable and secure platforms to ensure the full functionality of the system. As emphasized in the White Paper on Industry 5.0, the ongoing evolution of these technologies demands a human-centric approach, ensuring that AI contributes not only to process automation but also to the reinforcement of human values, creativity, and societal well-being [234].

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
BAS	Building Automation System
BIM	Building Information Modelling
BMS	Building Management System
CO2	Carbon Dioxide
CoAP	Constrained Application Protocol
CotS	Commercial Off The Shelf
CV	Computer Vision
DGT	Digital Transition
DL	Deep Learning
DT	Digital Twin

EnT	Energy Transition
FDD	Fault Detection and Diagnosys
FP2	Flagship Project 2
GAM	Generative Addtive Model
GBR	Gradient Boosting Regression
GIS	Global Information System
H&BP	Health and Biopharma
HTTPS	HyperText Transfer Protocol Secure
HVAC	Heating, Ventilation and Air Conditioning,
IoT	Internet of Things
LIME	Local Interpretable Model-Agnostic Explanations
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
ONVIF	Open Network Video Interface Forum
PM	Particulate Matter
PMV	Percivied Mean Vote
PPD	Predicted Percentage of Dissatisfied
PPE	Personal Protective Equipment
RAG	Retrieval-Augmented Generation
RFC	Request for Comments
SHAP	SHapley Additive exPlanations
SQL	Standard Query Language
SVM	Support Vector Machine
TRL	Technology Readiness Level
tVOC	total Volatile Organic Compound
UN	United Nations
UNEP	United Nation Environmental Programme
YOLO	You Only Look Once
WSL	Windows Subsystem for Linux

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