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AI-enhanced BIM Systems for Real-time Energy Performance Simulation

Lin Yang*

Lin Yang, Inner Mongolia University of Science & Technology, Baotou, Inner Mongolia

*Corresponding author: Lin Yang, email: leo.crystalcg@gmail.com

Abstract

Amid urgent climate goals, the building sector's high energy use demands smarter design and operation strategies. This paper critically explores recent peer-reviewed literature on AI-enhanced Building Information Modeling (BIM) systems for real-time energy performance simulation, highlighting how artificial intelligence (AI) techniques are integrated with BIM to improve building energy efficiency, reviewing global studies that combine BIM-based energy modeling with machine learning, optimization algorithms and digital twin frameworks. Key findings indicate that AI can dramatically accelerate energy simulations and enable real-time predictive analysis in both design and operational phases. Surrogate models (neural networks and gradient-boosted trees) trained on BIM-generated data achieve prediction accuracies above 90%, providing instant feedback on design alternatives. In operation, AI-driven digital twins linking BIM with IoT sensor data allow continuous monitoring and predictive control of building systems. These approaches have led to significant energy savings (often >10%) and support net-zero energy goals. However, challenges persist in data interoperability, model generalization and industry adoption. This paper contributes an integrated perspective on current methods, empirical outcomes and emerging themes (explainable AI and uncertainty analysis), outlining future research directions to fully realize real-time energy simulation in smart sustainable buildings.

Keywords

Artificial Intelligence (AI); Building Information Modeling (BIM); Real-Time Energy Simulation; Digital Twin; Machine Learning; Sustainable Building Design.

1. Introduction

Energy efficiency in buildings has become a paramount concern globally as buildings account for roughly 36–40% of annual energy consumption and a significant share of carbon emissions (Min et al., 2022). Improving building energy performance is crucial for meeting climate targets such as the Paris Agreement. Building Information Modeling (BIM) is now an established tool in the architecture, engineering and construction (AEC) industry, providing detailed digital representations of a building's geometry and systems throughout its lifecycle. According to Liu et al.' (2019), BIM facilitates traditional building performance simulations (BPS) including energy modeling, by supplying rich data on building envelope, materials and systems. Conventionally, engineers use BIM exports in physics-based simulation engines (EnergyPlus) to predict energy consumption, thermal comfort, daylight and key performance metrics (Gourlis, 2023). However, these simulations can be computationally intensive and are typically done in batch processes for static scenarios, rather than continuously in real time. In parallel, the rise of artificial intelligence (AI) and data-driven methods offers new opportunities to enhance BIM-based analysis. AI techniques particularly machine learning (ML) algorithms can learn complex patterns from simulation data or real sensor data, providing fast predictive

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models (surrogates) of building performance (Cecoon & Villa, 2021). This convergence has given birth to the concept of AI-enhanced BIM intelligent systems and platforms where BIM's structured building data is combined with AI algorithms to simulate and even optimize energy performance more efficiently. A related development is the digital twin, a virtual replica of a physical building that continuously receives data from IoT sensors and uses AI to mirror and predict the building's performance in real time (Sepasgozar et al., 2023). These innovations promise to shift energy analysis from a one-off design exercise to a continuous, adaptive process across the building lifecycle.

Moreover, traditional energy modeling workflows face limitations that AI integration aims to overcome. First, exploring multiple design alternatives for energy efficiency is time-consuming; each option must be individually modeled and simulated, leading to a narrow search of the design space (Tsikas et al., 2025). This is problematic in early design when decisions have profound impacts on future energy use. Second, conventional simulation tools often operate in silos, not fully interoperable with BIM, causing manual data transfer and potential errors (Panagoulia & Rakha, 2023). Third, building operations rarely adhere to design assumptions where real occupancy patterns and weather deviations cause a performance gap between predicted and actual energy use (Mahdavi et al., 2021). Static simulation models struggle to adapt to these dynamic conditions, through introducing AI, researchers hope to automate and accelerate simulations and to enable real-time performance assessment, thereby supporting more informed decision-making. For example, a trained ML model can instantly predict annual energy use for a given set of design parameters, allowing designers to get immediate feedback on efficiency improvements as identified in Seyedzadeh et al.'s (2018) literature review. Similarly, an AI-driven digital twin can continuously forecast a building's energy demand and optimize control settings (like HVAC adjustments) in response to live data (Tsikas et al., 2025). Thus, the rationale for this research is that combining BIM with AI has the potential to significantly improve both the speed and intelligence of energy performance simulations, which is critical for sustainable design and operations in an era of smart cities and climate urgency.

2. Current Situation of Study

Research interest in integrating AI with BIM for energy applications has surged in recent years. De Wilde (2023) suggests that the fields of AI, machine learning and digital twins have rapidly permeated the building simulation domain, which historically relied on physics-based models. In fact, digital twin concepts only started appearing in building performance literature around 2017, but have grown exponentially since 2018 as figure 1 illustrates this trend where academic publications on digital twins for building energy have increased dramatically, especially in leading countries like China as increasing studies now explore AI applications at different stages of the building lifecycle. In early-design phases, researchers have developed frameworks to link BIM with automated energy simulations and optimization. Khan et al. (2024) propose a system that generates a dataset via BIM-driven simulation, trains an ML model to predict energy outcomes, and then runs multi-objective genetic algorithms for design optimization. Such approaches have achieved high prediction accuracy (R^2 > 0.93) and identified design improvements yielding ~13% energy savings in case studies. Other works use surrogate models to evaluate numerous design variants rapidly, as Tsikas et al. (2025) trained regression, decision tree, random forest and neural network models on BIM-generated data for 337 residential building cases, finding that an ANN could best predict energy use instantly with minimal error.

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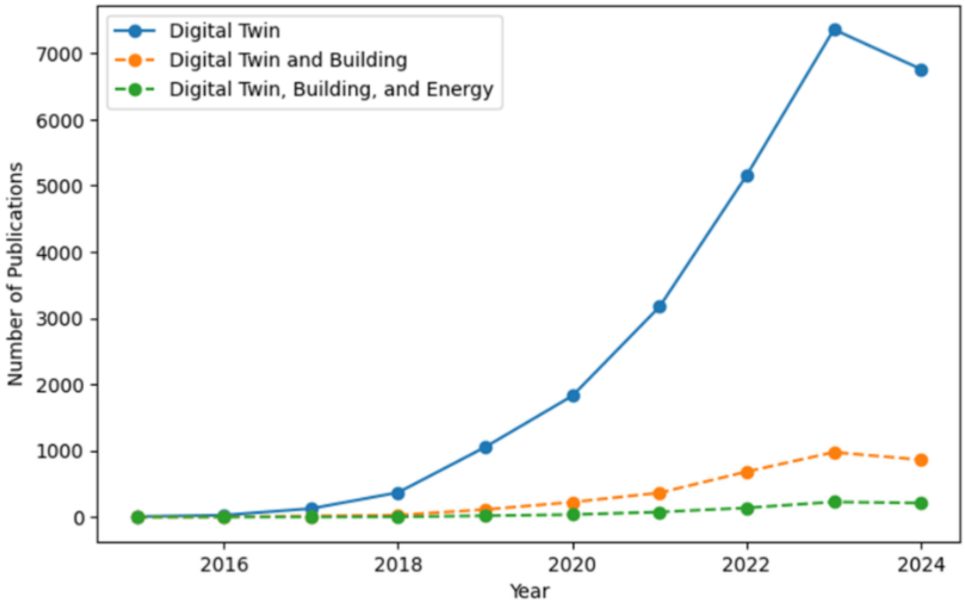

Figure 1. Trends in publications on digital twin, building and energy over the years (Sghiri et al., 2025)

Additionally, there is growing interest in applying AI during building operation through digital twins. Pioneering projects (Agostinelli et al. 2021 in Italy) have created district-scale digital twins where BIM is integrated with real-time sensor data and AI analytics to manage energy systems in real neighborhoods. These efforts showed that AI algorithms can optimize energy flows while maintaining comfort by evaluating renewable energy and storage scenarios to move a community closer to net-zero energy consumption. Despite this progress, the adoption gap in practice remains notable. Literature reviews highlight that while dozens of conceptual frameworks and pilot studies exist, few have been fully implemented at scale in industry settings according to Sghiri et al. (2025). The integration of BIM, building energy modeling (BEM) tools, IoT platforms and AI is also highly complex, often requiring bespoke solutions. There is also skepticism regarding reliability where facility managers may be wary of trusting "black-box" AI predictions for critical decisions like HVAC control without clear explanations or proven robustness, hence emerging research into explainable AI in this domain (Kahn et al., 2024). Additionally, data availability and quality can be limiting factors where AI models need rich training data, which in design can be synthetically generated via simulations, but in operation relies on extensive sensor deployments. These gaps indicate that further research and development are needed to translate AI-enhanced BIM from promising concept to common practice.

3. Research Gap, Aims, Objectives and Contributions

While current research demonstrates the feasibility and benefits of AI-integrated BIM systems, significant gaps remain in knowledge and practice. One gap is a lack of unified frameworks and standards for interoperability: many studies use custom workflows to connect BIM models with energy simulation engines and AI toolkits, which may not generalize easily (Agostinelli et al., 2021). For example, transferring a BIM model into a simulation requires handling geometry and material data (often via formats like gbXML or IFC), and mismatches in data schemas can impede automation (Kahn et al., 2024). Another gap lies in real-time performance where true real-time energy simulation would entail continuously updating models with live data and instantly computing control actions, yet most case studies are still in quasi-real-time (running predictions on intervals of minutes or hours) and often focus on either the design stage *or*

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operational stage, but not both. Thus, bridging this design-operation divide is an open challenge. Moreover, there is a research gap in validating AI-driven predictions against long-term actual building performance, as few studies report on multi-year deployments of digital twins or how AI models degrade or adapt over time in a changing building context. This gap in longitudinal evidence makes it harder to quantify the reliability and ROI of such systems. Finally, much of the literature has been technology-driven, with less focus on human and organizational factors, for instance, how to effectively present AI simulation results to architects or facility managers (usability) and how to upskill practitioners to trust and leverage these advanced tools. Overall, the current body of research lacks a comprehensive understanding of how to standardize, scale and sustain AI-enhanced BIM energy simulation in real-world projects, which this report addresses by synthesizing findings and pointing out these critical needs.

The aim of this report is to provide a comprehensive academic synthesis of AI-enhanced BIM systems for real-time energy performance simulation. These objectives are designed to aid the achievement of the proposed research aim. 1) To review the methods researchers have used to integrate AI (machine learning, optimization algorithms) with BIM and energy modeling, covering both design-phase and operation-phase applications. 2) To analyze empirical results from case studies and experiments worldwide, demonstrating the effectiveness of AI-enhanced BIM (such as accuracy gains, time savings, or energy reductions achieved). 3) To identify common themes, benefits and challenges found across the literature like faster simulations and debates such as the trade-off between model accuracy and interpretability. 4) To formulate future research directions and recommendations that can guide academic inquiry and practical development toward more effective real-time energy simulation in smart building systems. By fulfilling these objectives, this paper contributes to academic knowledge by consolidating scattered findings from the rapidly evolving intersection of BIM, AI and building energy simulation. While prior reviews have examined related areas in data-driven building energy prediction and BIM-based performance modeling (Tsikas et al., 2025), this synthesis uniquely focuses on the convergence of AI with BIM for real-time simulation, reflecting the state-of-the-art up to 2025. Practically, the insights presented can inform stakeholders including architects, engineers, energy modelers and facility managers about the potential of AI-enhanced BIM workflows and what benefits can be expected. By also discussing challenges, this report guides technology developers and policymakers on where to focus efforts, thereby supporting both the academic discourse and the AEC industry’s advancement toward smarter, energy-efficient buildings.

4. Findings and Discussion

Bringing together the findings from the literature, several key themes in AI-enhanced BIM systems for real-time energy simulation are identified including (1) Accelerated simulation and design optimization via AI surrogates, (2) Digital twin implementations for real-time monitoring and control, (3) Data integration and interoperability challenges, (4) Model accuracy, validation and explainability, and (5) Energy performance outcomes and improvements achieved. The following sections will discuss each, highlighting consensus, debates, and representative studies and include empirical figures to illustrate these concepts.

5. Accelerating Simulation and Optimizing Design with AI Surrogates

One of the clearest benefits reported is the drastic acceleration of performance evaluation during building design by using AI as a surrogate for physics-based simulations. In conventional design processes, evaluating the energy impact of different design choices (orientation, form, materials, HVAC systems) requires separate simulation runs for each variant, which is labor-intensive (Di Santo et al., 2023). AI models can learn from a set of simulated cases and then predict outcomes for new design inputs almost instantly. This enables what-if analysis and optimization to be done in minutes rather than days. Numerous studies validate this approach, as Tahmasebinia et al. (2022) integrated BIM tools with regression modeling to evaluate green building designs; their approach identified certain building shapes (notably triangular forms) as particularly energy-efficient, in line with simulation results. Tsikas et al. (2025) directly compared multiple ML algorithms as surrogates and found ANN models provided the best fidelity, with error distributions tightly clustered around zero, outperforming simpler methods like linear regression. Figure 2 shows the error distribution of such models from their study, The curves represent error frequency (density) for four models: Statistical Regression (grey), Decision Tree (orange), Random Forest (green) and Artificial Neural Network (blue). The ANN shows errors tightly centered around 0, indicating high accuracy in reproducing detailed simulation results. In contrast, simpler models like regression have broader distributions (e.g. ±1 MWh error range), emphasizing the superior predictive performance of advanced AI techniques. The ANN's error curve is sharply peaked at zero, indicating very minor deviation from the ground-truth simulation results, whereas other models (basic statistical regression) show broader error spread (under- or over-predicting in some cases). This high accuracy means designers can trust the surrogate model to evaluate design tweaks in real time.

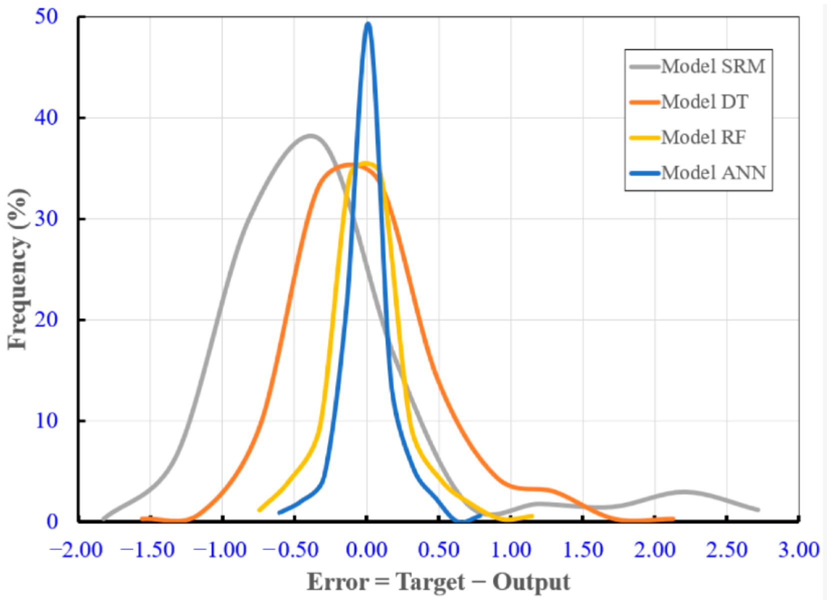

Figure 2. Prediction error distributions for various surrogate models trained to estimate building energy performance from BIM data (Tsikas et al. 2025).

Similarly, Khan et al. (2024) reported R^2 values above 0.93 for an optimized LightGBM model predicting energy use, leveraged this in an optimization loop to improve a building's design. The ability to incorporate multi-objective optimization is another advantage, as AI surrogates compute results so fast that algorithms can iterate thousands of design options to find Pareto-optimal solutions balancing energy, cost and. Other studies echo these successes including Li et al. (2024) used an orthogonal testing method with BIM and found optimal combinations of envelope parameters that reduced annual energy by significant margins (over 20% in some scenarios). In all, there is strong agreement that AI-enhanced BIM tools markedly speed up the exploration of design alternatives, allowing more thorough optimization for energy efficiency at early stages when changes are easier and cheaper to make. Alongside these benefits, a point of discussion is model generalizability. While an AI model can accurately predict within the range of designs it was trained on, several authors caution that predictions may be unreliable if a new design falls outside the training data distribution (Tsikas et al., 2025). This raises the

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importance of building robust and diverse training datasets (covering various building types, climates) or using adaptive learning.

Some debate also exists on the choice of algorithms, for instance, an ANN might give best raw accuracy but can be a "black box," whereas a decision tree or simpler regression might be more interpretable for designers (Hassija et al., 2024). Recent work strives to get the best of both worlds by employing explainable AI (XAI) techniques, as Khan et al. (2024) incorporated the LIME explanation tool with their ML model to identify which input features (design variables like HVAC efficiency, window-to-wall ratio, insulation levels) were most influential on predicted outcomes. This is valuable as it provides human designers insight into why the model suggests certain design improvements, thus building trust in the AI recommendations. In summary, recent empirical literature concurs that AI surrogates are a game-changer for early design analysis, as ongoing research is focusing on enhancing their reliability (through broader training and uncertainty analysis) and interpretability (through XAI), which will be crucial for industry uptake.

6. Real-time Monitoring and Control Via Digital Twins

The second major theme is the use of AI within BIM-based digital twins for operational energy management. Traditional BPS is largely an offline, design-stage activity. Digital twins extend BIM into the operational phase by linking it with live data streams, essentially turning the static BIM model into a dynamic simulation that runs in parallel with the real building (Wang et al., 2022). The findings across studies consistently show that digital twins enable real-time or near-real-time monitoring, anomaly detection and even predictive control of building systems. For example, a digital twin can continuously simulate expected energy performance under current conditions (weather, occupancy) and flag deviations if the actual consumption drifts, indicating a fault or inefficiency (Clausen et al. 2021 demonstrated this for public buildings, using a twin to improve energy efficiency and occupant comfort by detecting irregular HVAC behavior). AI is the "brain" in these systems: machine learning models process the incoming sensor data to make predictions (e.g. tomorrow's cooling load by Abbasabadi & Ashayeri, 2024) or decisions (e.g. adjust setpoints to shave peaks). A clear consensus is that **r**eal-time analytics are essential because building performance is highly dynamic, static schedules or models result in either wasted energy or comfort issues when conditions change unexpectedly (Boje et al., 2023).

Studies in different regions report positive outcomes from AI-driven real-time control. In the Rome digital district case (Agostinelli et al. 2021), the AI-enhanced twin allowed evaluating various energy management scenarios (like increasing solar PV capacity versus adding battery storage) and provided an optimized strategy that raised the self-consumption of renewable energy and met near-zero energy targets for the community. Another example by Péan et al. (2022, as reported by Arowoiya et al. 2024) involved a digital twin for a university building which, through reinforcement learning (a form of AI), learned to pre-cool or pre-heat the building in anticipation of occupancy, cutting down peak grid load without sacrificing comfort (illustrating proactive control). An example of an ideal digital twin for single building indoor environment by Arowoiya et al. (2024) is shown in Figure 3 below. A key real-time application is predictive maintenance by analyzing equipment performance data, AI can predict failures or inefficiencies, prompting maintenance before energy waste occurs. This was also identified as a key role of digital twins in multiple reviews where a chiller's power draw pattern might indicate refrigerant leakage, as an AI model can catch that anomaly and alert operators, preventing prolonged inefficiency (Agostinelli, 2024).

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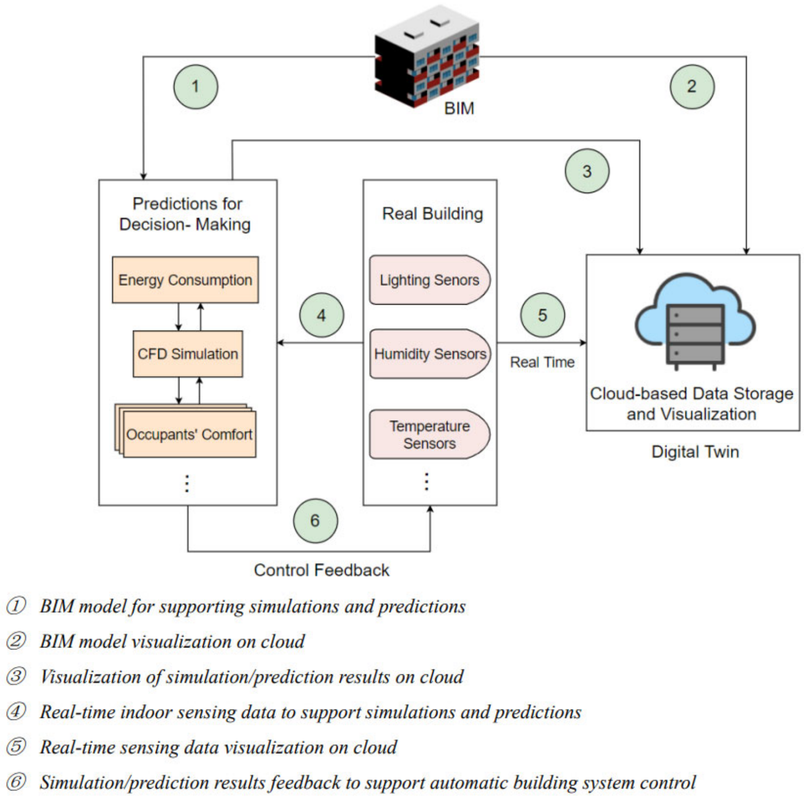

Figure 3. Example of an ideal digital twin for single building indoor environment (Arowoiya et al., 2024)

However, the literature also identifies significant challenges in achieving real-time capabilities. One challenge is data integration latency and ensuring that sensor data flows into the BIM/AI system rapidly and reliably enough for real-time decisions (Rane, 2023). Edge computing approaches, as used in the Rome case, are one solution to minimize cloud communication delays (Agostinelli et al., 2021). Another challenge is the sheer volume of data in large buildings where AI models must be efficient to run continuously (Farzaneh et al., 2021). Scalability is thus a concern given that current case studies are often limited to one building or a small campus, and it remains an open question how a city-wide deployment of building digital twins might be managed, as Sghiri et al. (2025) flagged scalability and data privacy as critical challenges hampering wider adoption). Despite these issues, there is an optimistic outlook that as IoT infrastructure improves and cloud platforms mature, AI-driven digital twins will become more commonplace. Researchers are actively working on frameworks (often employing open standards like BIM IFC, MQTT for data, etc.) to make integration easier (Agostinelli et al., 2021). Governments and industry are also increasingly interested in digital twins for smart cities, which will likely accelerate development in the building energy domain as well. Nonetheless, De Wilde (2023) questions how much of the digital twin concept is genuinely new versus a rebranding of existing building simulation and control techniques. Traditional building automation systems have long used feedback control and sensor data. the novelty in digital twins is arguably the tighter BIM integration and more advanced analytics (AI/ML). While most authors hype digital twins as transformative, de Wilde (2023) urges a critical view to ensure these systems deliver substantively better outcomes, not just new jargon. So far, early evidence from the field is promising in terms of energy savings and operational insights, but long-term studies will be needed to fully convince practitioners of their value.

ISSN: 2710-0588

7. Data Integration and Interoperability

Another recurring research theme which is often underemphasized next to AI performance metrics, is the challenge of connecting BIM with energy simulation tools and operational data systems according to Banihashemi et al. (2022). Several studies have also discussed the interoperability issue where BIM models are rich but were not originally conceived for energy analysis, thus extracting the necessary data for simulation or linking with external databases can be non-trivial (Kahn et al., 2024). In the design phase context, one solution has been the development of automated workflows or middleware that convert BIM data to input formats of energy engines (gbXML, IDF, etc.). Research by Gao et al. (2019) reviewed such BIM-to-BEM integration and highlighted that mismatches (e.g. naming conventions, level of detail) often require manual fixes. Newer tools and standards (like the IFC schema for energy or APIs in tools like Revit's Insight) are improving this, and studies like Meng et al. (2021) explicitly dealt with developing workflows to ensure data consistency between BIM and the energy model. In operational digital twins, the interoperability challenge extends to real-time data ingestion via linking building management systems (BMS) or IoT sensor networks with the BIM model. A common approach is to use the BIM model as a static reference (for geometry, system mappings) and create a separate data platform where time-series data is stored and analyzed, with pointers back to BIM elements, for example, using a unique ID to link a temperature sensor's data to a specific room object in BIM (Agostinelli et al., 2021). Additionally, some frameworks use the MQTT protocol or other IoT standards to collect data, and then map it to BIM through middleware (Chamari et al., 2023).

The findings suggest that open data standards are critical to success. Several authors recommend using IFC (Industry Foundation Classes) for sharing models between software (van Berlo et al., 2021) and Brick or Haystack schemas for sensor metadata (Fierro et al., 2020). In practice, many case studies still report custom integration e.g., Agostinelli et al. (2021) had to manually connect their BIM (in Revit/InfraWorks) with various analysis tools (MC4 Suite for energy, Autodesk CFD for airflow, etc.) due to a lack of a unified platform. This indicates a gap where tool vendors and standards bodies need to catch up. Interoperability extends also to combining various simulation domains as some projects integrate not just energy simulation but also CFD (for airflow distribution) or renewable energy system simulation, all linked via the BIM model (Shirowzhan et al., 2020). Thus, ensuring all these pieces talk to each other is non-trivial and often a research contribution in itself in these papers. Moreover, one positive trend is the emergence of platforms and middleware aimed at easing integration. For instance, Dinis et al. (2022) used the BIMServer or ontology-based approaches to create a unified representation of building data that AI algorithms can consume. Recent works by Fernandes et al. (2024) created APIs that allow real-time queries to BIM models for properties needed in energy calculations, which can then be plugged into AI code. The consensus is that without addressing data interoperability, the most advanced AI models will not be practically deployable. Therefore, many of the papers reviewed explicitly mention their data handling strategy, and many call for "future development of unified BIM-Digital Twin frameworks" as a priority. This is clearly an area where academic research intersects with software development and standardization efforts.

8. Model Validation, Accuracy and Explainability

According to Khan et al.'s (2024) study, high accuracy metrics are reported for their AI predictions of energy performance with ANN models achieving <5% error on test data. When combined deep learning approaches predicting hourly loads with errors in the 5–10% range as reported by Sajjad et al. (2024) *al.* (2017). Although these results are encouraging, researchers are careful to validate models on separate test sets or via cross-validation to ensure they

ISSN: 2710-0588

generalize. A few studies went further to validate AI predictions against real monitored data (when available). For example, Amasyali & El-Gohary (2018) compiled numerous data-driven prediction studies and found that while many ML models perform excellently on historical data, their performance can degrade if building usage changes or if applied to a different building. Thus, the concept of transferability emerges, questioning whether a model trained on one building or scenario be used on another. Most AI-BIM works train models per building or per design scenario, which limits direct transfer, but some propose transfer learning techniques to adapt models to new contexts, representing an area of ongoing research (Casapulla et al., 2025). Explainability of AI models is another point of focus as mentioned by Khan et al. (2024), using LIME to provide local interpretability of their gradient-boosted tree model. The result was a chart of feature importance for each prediction, which helped identify that HVAC system coefficient of performance and window glazing properties were among the most influential factors for energy consumption in their case study. Such insights are valuable as only a few studies discovered counter-intuitive influences (e.g. a certain design parameter had a nonlinear effect) which were then examined further through explainability tools (Kahn et al., 2024).

The literature seems to agree that black-box models, while powerful, need to be demystified for end-users according to Sabeena (2025). This is especially true if an AI is to suggest operational changes in a building, where facility managers will want to know *why* the AI recommends, say, turning off a certain chiller for an hour. Techniques like rule extraction from trained models or hybrid physics-AI models (grey-box models) are being explored to inject more transparency. Another aspect of validation is uncertainty analysis. Only a few cutting-edge studies address this, but it’s worth noting: Khan et al. (2024) introduced uncertainties (weather variability, occupant behavior uncertainty) into their optimization and found that accounting for uncertainty could further improve robust energy savings (an additional 4% improvement beyond the deterministic optimum). This indicates that rigorous approaches are being developed to ensure AI recommendations are not just optimal for a fixed scenario, but resilient to variations, representing a crucial aspect for real-world reliability. Similarly, some digital twin studies used ensemble models or continuously recalibrating models to maintain accuracy over time (Karkaria et al., 2025). These advanced validation strategies are not yet standard, but they represent an evolving best practice. In sum, the field is moving from simply proving that “AI can match simulation” to ensuring “AI can be trusted and understood”. The consensus is that high accuracy is necessary but not sufficient as stakeholders need confidence in AI outputs. Through methods like explainability, uncertainty quantification and continuous validation, researchers are addressing this which represents an important development for eventual industry adoption.

9. Energy Performance Outcomes and Improvements

Ultimately, the goal of these AI-enhanced systems is to improve energy performance of buildings. The literature provides evidence of significant potential improvements, though often in simulated or controlled scenarios rather than measured post-occupancy savings (Peinturier & Wallom, 2025). A common claim is that by exploring more design options or by optimizing controls, energy consumption can be reduced on the order of 10–30% compared to standard practice. For instance, Khan et al. (2024) reported a 13.4% reduction in energy use (with simultaneous improvements in CO_2 emissions and thermal comfort) for a case building after their AI-driven optimization. Li et al. (2024) similarly showed double-digit percentage reductions in annual energy demand by selecting optimal design parameters via a BIM+AI approach. These are non-trivial savings, especially considering many developed countries are seeking on the order of 20-30% building sector improvements to meet climate targets by 2030. Case studies of operational optimization also report benefits as digital twin projects often highlight peak load reduction or better load balancing rather than just absolute energy kWh

ISSN: 2710-0588

savings (Li & Hong, 2025). Moreover, one case achieved a flattening of the daily load curve, reducing peak demand by ~15% which can lower utility costs and strain on the grid (Shirazi & Jadid, 2017), and another reported benefit is improved occupant comfort alongside energy efficiency as the Clausen *et al.* (2021) digital twin framework managed to reduce HVAC energy by ~10% while keeping more stable indoor temperatures by predicting issues ahead of time.

It's also noteworthy that AI-enhanced simulations support net-zero energy building (NZEB) designs more holistically. Sajjad et al. (2024) addressed net-zero tall buildings and found that BIM-driven energy simulation (even without explicit AI in their case) strongly correlates with achieving net-zero goals when integrated early in design. Moreover, adding AI to that could further refine how those buildings are designed and operated to maintain net-zero balance. Early applications of AI for renewable energy integration within buildings (optimizing when to use stored solar energy vs. grid) have been demonstrated in digital twin research (Fan & Li, 2023), emphasizing that beyond reducing consumption, AI can help intelligently manage production and storage to hit NZEB targets. However, many empirical studies reported savings are from simulations or limited pilots as real buildings might see performance gaps (Zhao et al., 2022; Guo &Wei, 2016). For example, a design optimization might presume ideal occupancy patterns, whereby if actual behavior differs, the real savings might be lower (Zhao et al., 2022). However, since digital twins allow recalibration with actual data, they provide a mechanism to keep performance on track, which traditional design-stage simulation cannot do. Over multiple studies, a general finding is that AI-enhanced BIM systems help close the performance loop according to Elmousalami et al. (2025), whereby design intentions are more likely to be achieved in operation when continuous simulation and adjustment is in place. This continuous commissioning aspect could lead to sustained efficiency improvements in the long run, an insight strongly emphasized in digital twin literature (Sghiri et al., 2025).

Figure 4 below (drawing on data from a 2025 review) shows the empirical outcomes from roles and applications of digital twins and their impacts in Sghiri et al.'s (2025) systematic literature review. Fifteen recent digital-twin case studies are summerised into a single comparative table, showing how real-time BIM-based simulation underpins energy management across HVAC, lighting, renewable microgrids and even specialist contexts such as animal housing. Each row traces a clear line from the application area and building type through the live data that feed the twin combining IoT streams, BIM geometry, weather inputs and other operational records to the AI method deployed, which ranges from deep-learning forecasters (CNN-LSTM, LSTM) and graph neural networks to optimisation heuristics such as genetic algorithms and NSGA-II, together with the software environments in which they run (Sghiri et al., 2025). It is revealed that twins drawing on multiple data sources are already delivering pre-emptive energy savings by predicting loads and adjusting systems in advance, while single-source twins still contribute but mainly through retrospective analysis, it also highlights the field's methodological maturity, where advanced AI models are paired with optimisation routines to secure double-digit efficiency gains, align demand with on-site renewables and preserve occupant comfort. Overall, the evidence reinforces the review's central message that digital twins are becoming holistic, context-aware energy managers rather than narrow tools for shaving baseline consumption (Sghiri et al., 2025).

ISSN: 2710-0588

Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
Renewable energy	Not specified	√	None	√	None	CNN-LSTM	Not specified
Renewable energy	Not specified	None	None	√	Cooling system temperatures	LSTM	OPAL-RT Siemens Microgrid Controller
HVAC	Not specified	√	√	√	Current occupancy/environmental state	Genetic algorithm	Controleum, sMAP, ModestPy
HVAC	Office building	√	None	None	None	Machine Learning	Unity 3D Engine, FIWARE Context Broker
Lighting	Residential (smart homes)	√	none	None	Historical energy consumption data and home appliances	LSTM IWOA	Not specified
Multi-systems	Residential	None	None	√	Building-wide energy consumption data	Naïve, linear regression, LSTM, Prophet	Not specified
HVAC	Educational	√	√	None	Occupant surveys on comfort perception	GNN	Neo4j
HVAC	Residential (twin prototype homes)	√	None	√	None	NSGA-II	Energy Plus Open Studio JePlus+ EA
HVAC, thermal performance	Not specified	√	None	None	Historical building energy consumption data	None	Not specified
HVAC	Residential buildings	None	√	√	None	None	Insight, Autodesk REVIT
Simulation of energy performance	Commercial (pigsty)	√	None	√	None	None	Not specified
Energy performance simulation and modeling	Educational	√	None	None	None	ANN	Power BI MATLAB SketchUp TRNSYS
Thermal management	Test building, single room (25m^2), Singapore	√	None	None	Physical measurements from the test environment	Machine Learning	OpenModelica, Functional Mockup Interface, Python
HVAC	Smart buildings	√	None	√	Geometric and material properties created	Algorithm not specified	Not specified
HVAC	Commercial (office building)	√	None	None	None	None	Not specified
Renewable energy	Commercial (office building)	√	√	None	Thermal comfort survey data	ANN/MOGA	Revit C # Simulink MATLAB

Figure 4. Empirical summary of digital twin applications for predictive modeling and simulation (Sghiri et al., 2025)

In summary, the analytic synthesis of current research confirms that AI enhancements to BIM have demonstrated significant improvements in the speed and quality of energy performance simulation. They enable rapid design iteration, continuous operational tuning and integration of disparate data sources into a cohesive model of building performance. The academic consensus is positive about the potential where AI methods are largely seen as complementary to traditional simulation, not replacing physics but augmenting it to handle complexity and real-time demands. Debates remain on how to best implement these systems (standardization, trust, etc.), but there is little doubt that this convergence of technologies is a key part of the future of sustainable building engineering.

ISSN: 2710-0588

10. Conclusion

This comprehensive review reveals that AI-enhanced BIM systems are reshaping how we model, simulate and manage building energy performance. A first key insight is the dramatic improvement in simulation agility by training machine learning models on data from BIM-based simulations, researchers have achieved near-instantaneous energy predictions for design alternatives that would traditionally take hours of computation. This enables design teams to iterate more freely and explore innovative solutions (forms, materials, systems) with immediate feedback on energy implications. The second insight is the emergence of real-time building performance management through digital twins. Integrating BIM, sensor data and AI analytics yields a living model of the building that can continuously track and predict performance. Case studies demonstrate that such systems can detect anomalies, optimize control strategies and better integrate renewable energy, leading to more efficient and resilient building operations. Third, the synergy of BIM and AI also fosters a more integrated lifecycle approach to energy management: the same digital model can be used from early design (for simulation) through construction (for coordination) into operation (as a digital twin), creating a feedback loop where operational data informs future design improvements (a cornerstone of sustainable practice). Broad agreement on the energy and emissions benefits is also found to be attainable as AI-augmented optimization has yielded double-digit percentage reductions in energy use in various studies and improved alignment between predicted and actual building performance. Where a traditional approach might design an efficient building but see performance degrade due to unforeseen operational issues, an AI-driven twin can catch and correct those issues, keeping the building closer to its optimal performance. Additionally, the incorporation of explainable AI techniques is a noteworthy advancement, as it addresses the transparency gap where stakeholders can see which factors drive energy outcomes, making the technology's recommendations more convincing and actionable. Finally, this review highlights that these technologies are globally relevant, researchers worldwide converge on similar themes, indicating a coherent direction in academic inquiry and a shared recognition of buildings' pivotal role in climate mitigation.

11. Significance of Study

The findings are significant on multiple levels. Academically, they validate that combining data-driven AI methods with physics-based building simulation leverages the strengths of both, physics models ensure realism and compliance with laws of energy, while AI provides speed and adaptability. This hybrid approach is a paradigm shift in building performance analysis, moving the field towards what one might call "intelligent simulation", representing simulations that learn and improve over time. For the building industry and policymakers, the implications are equally significant. Buildings traditionally operate with static schedules and infrequent energy audits, but AI-enhanced BIM systems promise a future of continuous commissioning, where a building is constantly self-evaluating and tuning its performance. This could lead to substantial energy savings at scale if adopted broadly, as well as improved comfort and functionality of built environments (smart buildings that respond to occupants' needs in real time). The ability to quickly evaluate design options also means sustainable design need not be a slow, expensive process; even resource-constrained projects could afford to optimize designs if AI tools make simulation essentially free (in terms of time). Moreover, the integration of renewables and smart grids with buildings can be facilitated by these systems, a building that can forecast its energy use and adjust can better match its consumption with solar generation or respond to grid signals, supporting broader clean energy systems. Thus, these findings have relevance not just for individual buildings but for urban energy infrastructure and climate strategies. The research also identifies ancillary benefits as AI can handle the complexity of

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human behavior and other stochastic variables better than manual methods, so it offers a path to incorporate occupants into energy models more meaningfully (e.g. through occupancy prediction, adaptive comfort models). And by bringing together disciplines (IT, AI, building engineering), these efforts are pushing the AEC industry towards digital transformation – a necessary evolution for productivity and innovation in a traditionally conservative sector. In summary, the significance of this body of research is that it provides both the vision and some proof-of-concept examples of intelligent, responsive building systems that could substantially reduce energy waste and help meet global sustainability goals.

12. Limitations and Implications for Future Studies

Despite encouraging results, present studies remain narrow in scope, often validating AI-BIM surrogates on a single building type or climate and piloting digital-twin control for only weeks or months, which leaves generalisability, model drift, sensor recalibration and the lifetime cost of keeping BIM and IoT data in sync largely untested. Datasets rarely include extreme weather or atypical occupancy, so prediction bias emerges when conditions deviate, and fully connected buildings raise cybersecurity and privacy risks that few authors examine, computational training loads and specialist software still deter small firms, while business models that justify large-scale retrofits are thinly documented, and proprietary industry deployments that could offer practical insight seldom appear in academic sources. Thus, future work must develop open ontologies that tie IFC-based BIM, building-energy models, live sensor streams and AI outputs into one seamless framework, pursue hybrid physics-AI engines that blend machine-learning insights with first-principles heat-transfer equations to boost robustness and explainability, and refine reinforcement-learning controllers that can adjust HVAC and renewables in real time without compromising safety or comfort. Researchers should extend optimisation studies from single buildings to campuses and city districts, integrate digital twins with grid and storage models for demand response, and design visual and augmented-reality interfaces that help facility managers trust and act on AI recommendations. Longitudinal case studies that run for several years across diverse building types, climates and cultural contexts will be essential to measure durability, maintenance effort, and true energy savings, thereby moving AI-enhanced BIM from promising demonstration to reliable, scalable infrastructure for low-carbon, resilient buildings and communities.

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