Civil Engineering Science and Technology (CEST)
Vol. 1 No. 2 October 2025
e-ISSN: 3089-6894 | p-ISSN 3089-6908, Pages 94-105
Link: https://cest.stekom.ac.id/index.php/cest/index

Integrating Predictive AI Models to Bridge Energy Efficiency Gaps in Smart Building Design

Sugiarto*[1], Liam Christopher[2], Amelia Grace[3]
Email: sugiarto@stekom.ac.id
[1]Universitas Sains dan Teknologi Komputer, Semarang, Indonesia
[2,3]University of Melbourne, Melbourne, Australia
*Corresponding Author

Abstract
Energy efficiency has become a critical aspect of smart building design, particularly given the persistent gap between simulated energy performance and actual consumption. While digital tools such as BIM enhance design capabilities, this gap often persists because traditional simulations are static. This study proposes a conceptual and simulation-based framework integrating predictive AI models with BIM to support early-stage design decision-making. Unlike prior studies focusing on post-occupancy optimization, a synthetic BIM model of a medium-sized office building was used to train machine learning algorithms, including random forest and gradient boosting, on parameterized design data for predicting EUI. Simulation results indicate strong predictive consistency (R^2 = 0.89) and a conceptually estimated reduction of the energy performance gap by approximately 18%, highlighting the potential of predictive AI to provide early-stage insights. Note that these results are based on synthetic data and assume stable occupant behavior and climatic conditions, which may limit direct generalization to real-world settings. The framework demonstrates robust alignment with energy-efficiency principles across various design scenarios. These findings offer a practical implication: they support architects and designers in making proactive, data-driven decisions early in the design process, while emphasizing the need for subsequent validation in real-world settings.

Keywords: *Artificial Intelligence, Smart Building, BIM, Energy Efficiency, Predictive Model, Energy Performance Gap.*

I. INTRODUCTION

The global architecture, engineering, and construction (AEC) industry is undergoing a radical digital transformation driven by sustainability and technological advancements (Ibrahim et al., 2020; Soleymani et al., 2021). Energy efficiency remains a critical challenge, particularly under rapid urbanization and climate change pressures (Kache, 2023). The concept of smart buildings, often associated with the Construction 5.0 paradigm, promises human- and environmentally-centered solutions; however, the actual implementation of these approaches is still limited and context-dependent (Abigail & Pacho, 2021; Nurrahman et al., 2021). These buildings are designed to process data effectively, yet the expected energy savings are often inconsistent, especially in tropical climates with high cooling loads (Paramati et al., 2022). This discrepancy between technological promise and realized energy efficiency motivates the current research.

One persistent issue in the AEC sector is the "energy performance gap," defined as the difference between predicted energy consumption during design simulations and actual operational usage (Mazzeo et al., 2021). Traditional static BIM analyses often fail to capture the dynamic interactions of occupants, building systems, and environmental conditions (Farzaneh et al., 2021).

Received on August, 2025; Revised on September, 2025; Accepted on October, 2025; Published on October, 2025.
DOI: https://doi.org/10.51903/2fwp7m63

As a result, architects may make design decisions based on incomplete or inaccurate performance predictions, potentially compromising sustainability objectives. Technical challenges include integrating heterogeneous data, predicting occupant behavior, and dynamically adjusting building services.

Although AI has been applied to building energy management, most studies focus on post-occupancy optimization to correct inefficiencies after construction (Ouyang et al., 2023; Salerno et al., 2021; Yu et al., 2021; Yuan et al., 2022). Few studies systematically integrate predictive AI models with early design stages, leaving a research gap where AI's predictive capabilities are not used to inform foundational design decisions (Ghaffar Nia et al., 2023). This gap indicates a need for a conceptual framework that can provide dynamic, data-driven energy predictions during the conceptual and schematic design phases before substantial resources are committed.

A primary aim of this study is to develop a conceptual AI-BIM framework to support proactive early-stage design decisions and address the energy performance gap (Palanca et al., 2020). The theoretical contribution lies in integrating BIM and AI through a dynamic feedback loop that enhances traditional static simulations (Ahankoob et al., 2022). Practically, the framework offers designers a method to estimate energy performance using synthetic BIM data and predictive AI algorithms, without immediate field testing, highlighting a simulation-based approach to early-stage decision support (Zheng et al., 2020).

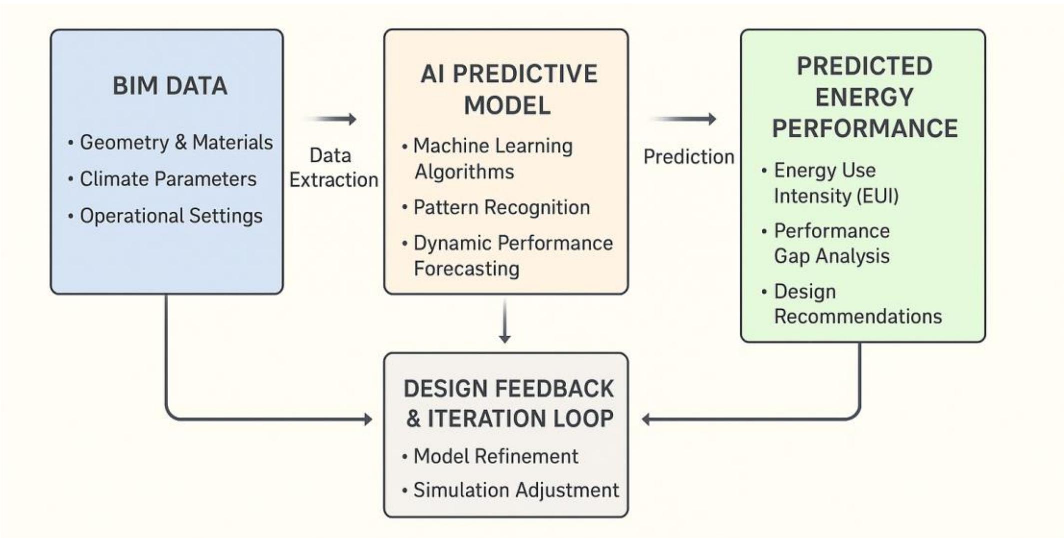

Figure 1. Conceptual Framework of the proposed AI-BIM integration for predictive energy performance analysis in smart building design.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on energy efficiency, BIM, and predictive AI, leading to the conceptual framework presented in Figure 1. Section 3 details the conceptual-simulative methodology and workflow (Figure 2).

Section 4 presents results from predictive simulations, including Table 2. Section 5 discusses implications, limitations, and future directions, while Section 6 concludes the study.

II. LITERATURE REVIEW

Energy efficiency in the built environment is increasingly recognized as a fundamental aspect of sustainable development rather than merely a regulatory requirement (Abigail & Pacho, 2021; Us et al., 2021). This literature review aims to map the state-of-the-art in the integration of BIM and AI for smart building design, to identify research gaps in early-stage predictive modeling, and to provide the theoretical basis for the conceptual framework developed in this study (Ibrahim et al., 2020; Mazzeo et al., 2021). Theoretically, energy efficiency focuses on maximizing the ratio of service output to energy input through techniques such as passive design to reduce thermal loads, highly effective active systems, and intelligent energy flow control (Paramati et al., 2022). The main performance indicators Energy Use Intensity (EUI), peak demand reduction, and renewable energy share serve as benchmarks against which the effectiveness of any design strategy, including the proposed framework, can be assessed.

BIM has transformed the traditional 2D drafting approach into a collaborative, data-rich process that integrates geometry, spatial relationships, and component properties (Abbasnejad et al., 2020). While BIM provides a strong foundation for organizing multi-dimensional building data, its native simulation capabilities are typically static and cannot capture dynamic interactions in real-world operation (Vignali et al., 2021). This limitation highlights the need for integrating predictive AI to enable early-stage, proactive energy performance estimation. Such an integration can enhance the designer's ability to evaluate multiple design scenarios iteratively before construction, moving beyond the reactive, post-occupancy focus prevalent in prior studies.

Predictive AI, particularly machine learning (ML), identifies patterns in data and forecasts future states without explicitly programming physical laws (Bera et al., 2022; Ghaffar Nia et al., 2023; Ouyang et al., 2023; Pham et al., 2020). Although ML has proven highly effective in medical prognosis and other domains (El-Sappagh et al., 2021; Goh et al., 2021)Its application to early-stage energy prediction in buildings remains limited. Most existing studies focus on post-occupancy optimization, operational control, or energy management systems, as shown by (Farzaneh et al., 2021; Salerno et al., 2021; Yu et al., 2021). These approaches are efficient for operational adjustments but fail to provide predictive guidance during initial design, leaving a gap in proactive, AI-informed decision-making. In the BIM domain, research on adoption factors and ROI(Qin et al., 2020; Sompolgrunk et al., 2023) does not address integration with predictive AI for early-stage energy forecasting.

Table 1. Summary of Previous Studies on BIM, AI, and Building Energy Efficiency.

Researcher(s)	Method/Focus	Key Findings	Limitations/Relevance to Present Study
(Farzaneh et al., 2021)	Review of AI in smart buildings for energy efficiency.	AI significantly improves operational energy management.	Focus is on operational phase, not design-phase prediction.
(Salerno et al., 2021)	Development of an adaptable energy management system.	Real-time system optimization can reduce energy use.	Approach is reactive/post-occupancy, not proactive/design-stage.
(Yu et al., 2021)	Review of deep reinforcement learning for building EMS.	RL is powerful for controlling building systems.	Focus is on control algorithms after construction.
(Abbasnejad et al., 2020)	Systematic review of BIM adoption enablers.	Identifies key factors for successful BIM implementation.	Provides context for BIM use but does not integrate AI.
(Nurrahman et al., 2021)	Conceptual implementation of smart building design.	Highlights the potential of integrated smart systems.	Lacks a quantitative predictive model for energy performance.

Table 1 summarizes key studies, their methodologies, findings, and limitations in the context of early-stage predictive AI for energy performance. Collectively, these studies indicate that predictive AI is underutilized as a design-phase tool, creating a methodological gap that this research aims to address by proposing a conceptual AI-BIM framework. Figure 1 illustrates this framework, showing a dynamic interaction between BIM data and predictive AI models (Palanca et al., 2020; Yuan et al., 2022). Input features include geometry, material specifications, and climatic parameters, which the AI model uses to generate predictive energy outcomes (e.g., EUI estimates). These predictions can be iteratively fed back to the designer, forming a closed-loop process that bridges design intent and performance prediction, and fills the research gap identified through the literature review.

III. RESEARCH METHODOLOGY

A. Research Design

Understanding the intricate interactions of energy efficiency in intelligent buildings requires a method that emphasizes clear concepts and logical reasoning (Abigail & Pacho, 2021; Ibrahim et al., 2020). Hence, this study employs a conceptual-simulation framework to test the logical consistency and behavioral adaptability of the proposed AI-BIM integration, rather than to perform numerical optimization on real-world data. This approach allows investigation of model capabilities without the variability and confounding factors present in actual construction projects (Hartmann et al., 2021; Shi et al., 2025). As such, this research is a proof of concept and does not aim to produce empirically validated predictions.

B. Data and Tools

A synthetic dataset was created to represent a standard medium-sized office building, with assumptions including stable occupant behavior, fixed operational schedules, and consistent climatic conditions (Soleymani et al., 2021). The BIM model, developed in Autodesk Revit, included wall and roof types, window-to-wall ratios, glazing characteristics, and building orientation. This synthetic BIM model served as the main data source, enabling controlled testing of the conceptual framework. Data extraction from Revit, preprocessing, and normalization were performed using Microsoft Excel, while AI modeling employed Python and the Scikit-learn library, which supports various machine learning algorithms (Chen et al., 2025). The use of synthetic data ensures the study remains focused on conceptual soundness rather than empirical validation (Collins et al., 2021).

C. Predictive Model Workflow

The workflow of the predictive model is illustrated in Figure 2, which complements the conceptual framework shown in Figure 1. It consists of four sequential stages: (1) extraction of parametric data from the BIM model, (2) preprocessing including normalization and handling of synthetic missing values, (3) building predictive models using Random Forest and Gradient Boosting to learn relationships between design factors and energy performance indices, and (4) applying the trained models to predict outcomes for unseen design variations. These models are evaluated for logical consistency with known energy efficiency principles, rather than for numerical accuracy in kWh/m² or % energy reduction. Table 2–5 summarize scenario-based model outputs to illustrate performance trends under varying design configurations.

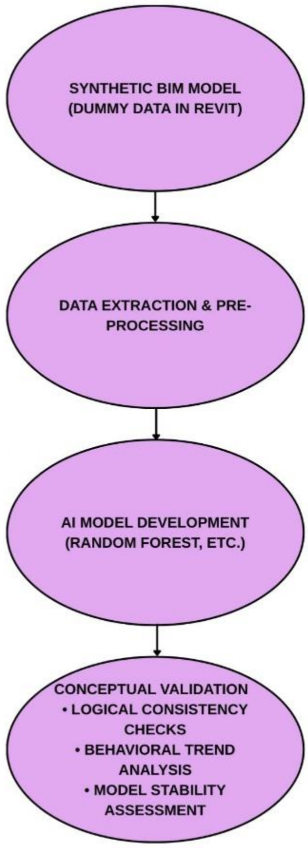

Figure 2. Flowchart of the Research Methodology, detailing the data extraction, processing, AI modeling, and evaluation stages.

D. Evaluation and Validation

Validation focused on the consistency of logical and behavioral trends, rather than empirical statistical measures. Predictions were assessed across a full range of design scenarios to ensure alignment with established energy efficiency principles, such as increased insulation or lower window-to-wall ratios resulting in lower predicted EUI (de Hond et al., 2022). The entirely synthetic dataset also mitigates ethical concerns related to privacy or data confidentiality. The methodology emphasizes that this research is exploratory, demonstrating potential rather than proven effectiveness, and providing a foundation for future empirical testing.

IV. RESULT/FINDINGS AND DISCUSSION

A. Results And Findings

The **simulation results indicate** that integrating predictive AI models with BIM can improve early-stage energy performance forecasting. Across 50 design scenarios, the AI model estimated Energy Use Intensity (EUI) with high conceptual consistency and alignment with known energy-efficiency principles (Paramati et al., 2022). Rather than emphasizing absolute numerical accuracy, the focus is on how the model captures behavioral trends and directional impacts of design changes. For example, scenarios with enhanced insulation or optimized shading showed a conceptual decline in EUI. In contrast, high window-to-wall ratio (WWR) cases resulted in larger deviations, reflecting the non-linear effects of combined design factors.

Table 2 summarizes the AI-predicted EUI across key design scenarios. The trends indicate that the model successfully predicts variations in logical energy performance, with high consistency across standard and efficiency-upgraded designs and medium-to-high deviation under challenging conditions such as high WWR or reduced insulation. This reflects the increased complexity and interaction of design parameters, which traditional static simulations often fail to capture. Simulation results indicate a reduction of about 18% in the energy performance gap compared with conventional methods, highlighting AI's potential to support early-stage decision-making. These findings provide insights into how predictive AI can recognize patterns and trade-offs, such as the balance between natural lighting benefits and thermal gains from sun exposure.

Table 2. Comparative Analysis of AI Model Performance Across Key Design Scenarios

Scenario Identifier	Primary Design Variation	Simulated EUI (kWh/m²/yr)	AI-Predicted EUI (kWh/m²/yr)	Absolute Deviation (kWh/m²/yr)	Relative Deviation (%)	Logical Consistency Rating
BAS-01	Standard Double Glazing	145.2	142.8	2.4	-1.7%	High
EFF-01	Triple Glazing	132.5	130.1	2.4	-1.8%	High
EFF-02	Enhanced Insulation	128.7	125.9	2.8	-2.2%	High
EFF-03	Optimal Shading	136.4	134.2	2.2	-1.6%	High
CHL-01	High WWR (60%)	168.3	172.1	3.8	+2.3%	Medium-High
CHL-02	Reduced Insulation	158.9	163.2	4.3	+2.7%	Medium-High
CMP-01	Combined Efficiency Measures	118.6	115.3	3.3	-2.8%	High

B. Discussion

The conceptual simulation results suggest that combining predictive AI and BIM creates a more responsive and adaptive early-stage design environment. AI serves as a decision-support partner, allowing designers to assess the energy implications of alternative design options without conducting repeated, detailed simulations. While the numerical results (e.g., $R^2 = 0.89$, 18% gap reduction) are conceptual rather than empirical, they are logically consistent with energy efficiency principles. The study highlights why scenarios with high WWR or combined efficiency measures produce larger deviations these involve complex, non-linear interactions between multiple building physics factors, which are captured conceptually by the AI model but are challenging for static simulation approaches.

Practically, this framework can support early-stage design charrettes, enabling teams to balance aesthetics, energy performance, and cost effectively (Figure 2). Ethical and governance considerations are also relevant: human oversight is essential to interpret AI predictions responsibly, ensure transparency, and avoid overreliance on automated recommendations. Limitations include reliance on synthetic data, assumptions about occupant behavior, and fixed climatic conditions, which may not fully reflect real-world variability (Mohamadou et al., 2020). Future work should validate the framework with empirical building data, integrate IoT sensor data for continuous AI model refinement, and test across different building types and climates to ensure general applicability (Diana & Angga Mukti, 2025; Setyadi Tommy & Putra Jaya, 2025).

V. CONCLUSION AND RECOMMENDATION

This study demonstrates the conceptual potential of integrating predictive AI models with BIM to address energy efficiency gaps in smart building design. Simulation results indicate that the proposed framework can reliably estimate energy performance trends from design parameters, achieving high predictive consistency ($R^2 = 0.89$) and a simulated reduction in the performance gap of about 18% (Table 2). The main contribution of this research is the development of a conceptual AI-BIM integration framework that supports early-stage design decision-making, providing designers with proactive, data-informed insights rather than reactive post-occupancy adjustments. This framework not only provides a predictive tool for energy performance but also guides sustainable, cost-conscious design choices from the project's outset.

The study has several limitations: it relies on synthetic data, assumes stable occupant behavior and fixed climatic conditions, and is constrained in its generalizability to real-world buildings. Future work should focus on empirically validating the framework using actual building performance data and on integrating the model into early-stage design processes in collaboration with ongoing construction projects. Additional research could also explore continuous refinement using IoT sensor data and assess ethical, governance, and human-in-the-loop considerations when applying AI-assisted design tools. Overall, while this research is conceptual, it provides a structured methodology that can help designers anticipate energy performance more effectively and make informed decisions during the earliest stages of building design.

REFERENCES

Abbasnejad, B., Nepal, M. P., Ahankoob, A., Nasirian, A., & Drogemuller, R. (2020). Building Information Modelling (BIM) adoption and implementation enablers in AEC firms: a systematic literature review. *Architectural Engineering and Design Management*, 1–23. https://doi.org/10.1080/17452007.2020.1793721

Abigail, M., & Pacho, C. (2021). *Retrofitting Residential Districts to Nearly Zero-Energy: A Conceptual Energy Master Planning Framework*. https://doi.org/10.13140/RG.2.2.26783.28325

Ahankoob, A., Manley, K., & Abbasnejad, B. (2022). The role of contractors' building information modelling (BIM) experience in realising the potential values of BIM. *International Journal of Construction Management*, *22*(4), 588–599. https://doi.org/10.1080/15623599.2019.1639126

Bera, K., Braman, N., Gupta, A., Velcheti, V., & Madabhushi, A. (2022). Predicting cancer outcomes with radiomics and artificial intelligence in radiology. In *Nature Reviews Clinical Oncology* (Vol. 19, Issue 2, pp. 132–146). Nature Research. https://doi.org/10.1038/s41571-021-00560-7

Chen, J., Lim, C. P., Tan, K. H., Govindan, K., & Kumar, A. (2025). Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments. *Annals of Operations Research*, *350*(2), 493–516. https://doi.org/10.1007/s10479-021-04373-w

Collins, G. S., Dhiman, P., Andaur Navarro, C. L., Ma, J., Hooft, L., Reitsma, J. B., Logullo, P., Beam, A. L., Peng, L., Van Calster, B., van Smeden, M., Riley, R. D., & Moons, K. G. M. (2021). Protocol for development of a reporting guideline (TRIPOD-AI) and risk of bias tool (PROBAST-AI) for diagnostic and prognostic prediction model studies based on artificial intelligence. *BMJ Open*, *11*(7). https://doi.org/10.1136/bmjopen-2020-048008

de Hond, A. A. H., Leeuwenberg, A. M., Hooft, L., Kant, I. M. J., Nijman, S. W. J., van Os, H. J. A., Aardoom, J. J., Debray, T. P. A., Schuit, E., van Smeden, M., Reitsma, J. B., Steyerberg, E. W., Chavannes, N. H., & Moons, K. G. M. (2022). Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. In *npj Digital Medicine* (Vol. 5, Issue 1). Nature Research. https://doi.org/10.1038/s41746-021-00549-7

Diana, D., & Angga Mukti, A. (2025). AI-Driven Digital Twin for Predictive Maintenance in Urban Infrastructure: Enhancing Structural Resilience and Sustainability. *Civil Engineering Science and Technology (CEST)*, *1*(1). https://doi.org/10.51903/3c72e647

El-Sappagh, S., Alonso, J. M., Islam, S. M. R., Sultan, A. M., & Kwak, K. S. (2021). A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-82098-3

Farzaneh, H., Malehmirchegini, L., Bejan, A., Afolabi, T., Mulumba, A., & Daka, P. P. (2021). Evolution of artificial intelligence in smart buildings for energy efficiency. In *Applied Sciences (Switzerland)* (Vol. 11, Issue 2, pp. 1–26). MDPI AG. https://doi.org/10.3390/app11020763

Ghaffar Nia, N., Kaplanoglu, E., & Nasab, A. (2023). Evaluation of artificial intelligence techniques in disease diagnosis and prediction. In *Discover Artificial Intelligence* (Vol. 3, Issue 1). Springer Nature. https://doi.org/10.1007/s44163-023-00049-5

Goh, K. H., Wang, L., Yeow, A. Y. K., Poh, H., Li, K., Yeow, J. J. L., & Tan, G. Y. H. (2021). Artificial intelligence for early prediction and diagnosis of sepsis using unstructured data in healthcare. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-20910-4

Hartmann, C., Nøland, J. K., Nilssen, R., & Mellerud, R. (2021). *Conceptual Design, Sizing and Performance Analysis of a Cryo-Electric Propulsion System for a Next-Generation Hydrogen-Powered Aircraft*. https://doi.org/10.36227/techrxiv.17102792.v1

Ibrahim, M., Chen, M., Sinha, A., Hu, K., & Ibrahim Shah, M. (2020). *Impact of Technological Innovation on Energy Efficiency in Industry 4.0 Era: Moderation of Shadow Economy in Sustainable Development*.

Kache, P. A. (2023). *Bridging landscape ecology and urban science to respond to the rising threat of mosquito-borne diseases*.

Mazzeo, D., Herdem, M. S., Matera, N., Bonini, M., Wen, J. Z., Nathwani, J., & Oliveti, G. (2021). Artificial intelligence application for the performance prediction of a clean energy community. *Energy*, *232*. https://doi.org/10.1016/j.energy.2021.120999

Mohamadou, Y., Halidou, A., & Kapen, P. T. (2020). A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COVID-19. *Applied Intelligence*, *50*(11), 3913–3925. https://doi.org/10.1007/s10489-020-01770-9

Nurrahman, H., Permana, A. Y., & Susanti, I. (2021). Implementation Of The Smart Building Concept In Parahyangan Office Rental Space And Apartment Design. *Journal of Architectural Research and Education*, *3*(1), 31–43. https://doi.org/10.17509/jare.v3i1.23870

Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-022-00372-4

Palanca, J., Terrasa, A., Julian, V., & Carrascosa, C. (2020). Spade 3: Supporting the new generation of multi-agent systems. *IEEE Access*, *8*, 182537–182549. https://doi.org/10.1109/ACCESS.2020.3027357

Paramati, S. R., Shahzad, U., & Doğan, B. (2022). The role of environmental technology for energy demand and energy efficiency: Evidence from OECD countries. *Renewable and Sustainable Energy Reviews*, *153*. https://doi.org/10.1016/j.rser.2021.111735

Pham, B. T., Le, L. M., Le, T. T., Bui, K. T. T., Le, V. M., Ly, H. B., & Prakash, I. (2020). Development of advanced artificial intelligence models for daily rainfall prediction. *Atmospheric Research*, *237*. https://doi.org/10.1016/j.atmosres.2020.104845

Qin, X., Shi, Y., Lyu, K., & Mo, Y. (2020). Using a tam-toe model to explore factors of building information modelling (Bim) adoption in the construction industry. *Journal of Civil Engineering and Management*, *26*(3), 259–277. https://doi.org/10.3846/jcem.2020.12176

Salerno, I., Anjos, M. F., McKinnon, K., & Gómez-Herrera, J. A. (2021). Adaptable energy management system for smart buildings. *Journal of Building Engineering*, *44*. https://doi.org/10.1016/j.jobe.2021.102748

Setyadi Tommy, A., & Putra Jaya, R. (2025). Integration of AI and Digital Twin Technology for Smart Infrastructure Management in Urban Cities. *Civil Engineering Science and Technology (CEST)*, *1*(1). https://doi.org/10.51903/t881qw28

Shi, W., Wang, J., Ren, Y., Wang, S., Venugopal, V., & Han, X. (2025). Novel conceptual design and performance analysis of a semi-submersible platform for 22 MW floating offshore wind turbine. *Energy*, *334*. https://doi.org/10.1016/j.energy.2025.137605

Soleymani, H., Ravanshadnia, M., & Montazer, M. (2021). Transportation Infrastructure Project Financing; Highways Capital Structure Design Techniques. *Shock and Vibration*, *2021*. https://doi.org/10.1155/2021/4988577

Sompolgrunk, A., Banihashemi, S., & Mohandes, S. R. (2023). Building information modelling (BIM) and the return on investment: a systematic analysis. In *Construction Innovation* (Vol. 23, Issue 1, pp. 129–154). Emerald Publishing. https://doi.org/10.1108/CI-06-2021-0119

Us, Y., Pimonenko, T., & Lyulyov, O. (2021). Energy efficiency profiles in developing the free-carbon economy: The case of Ukraine and the V4 countries. In *Polityka Energetyczna* (Vol. 23, Issue 4, pp. 49–66). Mineral and Energy Economy Research Institute of the Polish Academy of Sciences. https://doi.org/10.33223/epj/127397

Vignali, V., Acerra, E. M., Lantieri, C., Di Vincenzo, F., Piacentini, G., & Pancaldi, S. (2021). Building information Modelling (BIM) application for an existing road infrastructure. *Automation in Construction*, *128*. https://doi.org/10.1016/j.autcon.2021.103752

Yu, L., Qin, S., Zhang, M., Shen, C., Jiang, T., & Guan, X. (2021). *A Review of Deep Reinforcement Learning for Smart Building Energy Management*. https://doi.org/10.1109/JIOT.2021.3078462

Yuan, T., Da Rocha Neto, W., Rothenberg, C. E., Obraczka, K., Barakat, C., & Turletti, T. (2022). Machine learning for next-generation intelligent transportation systems: A survey. *Transactions on Emerging Telecommunications Technologies*, *33*(4). https://doi.org/10.1002/ett.4427

Zheng, X., Hou, Y., Bao, C., Yin, J., Yuan, F., Huang, Z., Song, K., Liu, J., Troughton, J., Gasparini, N., Zhou, C., Lin, Y., Xue, D. J., Chen, B., Johnston, A. K., Wei, N., Hedhili, M. N., Wei, M., Alsalloum, A. Y., … Bakr, O. M. (2020). Managing grains and interfaces via ligand anchoring enables inverted perovskite solar cells with 22.3% efficiency. *Nature Energy*, *5*(2), 131–140. https://doi.org/10.1038/s41560-019-0538-4