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MANAGEMENT IN REAL ESTATE: POWERED BY DIGITAL TWINS

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Received 15 June 2025; accepted 6 October 2025; published 30 December 2025

Abstract. The real estate industry, as a major contributor to global carbon emissions, is under intense pressure from investors and regulators to integrate environmental, social, and governance (ESG) criteria into its core strategy. However, managers of large, heterogeneous building asset portfolios commonly face a key challenge: how to make data-driven strategic decisions that enhance sustainability and energy performance in the absence of detailed operational data for most assets. Traditional ESG approaches often rely on static, variable-quality reports and lack the forward-looking, quantitative tools necessary for effective strategic decision-making and risk management. This paper aims to address this challenge by proposing and validating an innovative dynamic ESG management framework. The framework establishes a dynamic simulation environment by integrating Digital Twin (DT) and Deep Reinforcement Learning (DRL) technologies, aiming to enhance the dynamic capabilities of organisations for sustainable transformation systematically. Using 564 commercial buildings in Singapore as case studies, we conducted a multi-criteria scenario analysis of multiple Energy Conservation Measures (ECMs) to measure their combined impacts in terms of energy, cost, carbon emissions and occupant comfort. Findings show that the framework can provide decision support beyond traditional approaches, revealing non-intuitive management insights such as that reducing internal heat gain has a greater impact on total energy consumption than directly increasing heating, ventilation and air conditioning (HVAC) efficiency, and quantifying trade-offs between financial returns, carbon emission reductions and social outcomes (occupant comfort). The core contribution of this paper is that it demonstrates how cutting-edge digital technologies can be utilized to transform ESG management from a passive compliance reporting activity to a proactive, dynamic governance function centred on sense-capture-reconstruct, which managers can use to assess capital investments, validate sustainability paths, and effectively manage the This supports managers in evaluating capital investments, validating sustainability paths, and effectively managing the complex interplay between environmental, social, and financial performance.

Keywords: digital twin; ESG; building energy management; decision support; Singapore green building

Reference to this paper should be made as follows: Zhou, W., Krivins, A., Kaze, V. 2025. Management in real estate: powered by digital twins. *Entrepreneurship and Sustainability Issues*, 13(2), 280-298. <http://doi.org/10.9770/h9697726695>

JEL Classifications: O32, O36, Q01

1. Introduction

1.1 Background

With the real estate industry accounting for approximately 39% of global carbon emissions, of which asset and property management processes alone account for 28%, the industry is under intense pressure to improve its sustainability, given the growing global focus on sustainability and carbon neutrality goals (Boland et al., 2022), for managers of large commercial real estate portfolios, environmental, social, and governance (ESG) has evolved from a fringe topic to a core driver of strategy and value creation in the real estate industry (Ghisellini et al., 2018; SSGA, 2025; SuMi TRUST, 2024; Di Liddo, 2025). Global ESG assets are expected to exceed \$53 trillion by 2025, marking a fundamental shift in the market (ECOVIS, 2024). A combination of growing investor pressure drives this shift (Kastratović et al., 2024), tightening regulatory requirements (e.g., the EU's

Corporate Sustainability Reporting Directive CSRD), and widespread market recognition of the intrinsic link between sustainability performance and long-term financial returns and risk mitigation (Shahid et al., 2024; Yang et al., 2024).

The real estate sector is in the spotlight due to its large environmental and social footprint. The sector will account for approximately 34% of global energy-related CO₂ emissions in 2023, as well as around 34% of total global demand for energy (Global Alliance for Buildings and Construction, 2025). Decarbonization of the built environment is therefore essential to promote sustainable development and achieve global climate goals, such as those outlined in the Paris Agreement (Falana et al., 2024; Van Tam et al., 2024; Sebbaghi et al., 2025).

In this context, 'Twin Transition' - the intertwined and synergistic process of digital and green transformation - has become the dominant paradigm for realising a sustainable and competitive future (Rehman et al., 2023; Burinskienė & Nalivaikė, 2024; Razminienė & Tvaronavičienė, 2024; Baumgartner et al., 2025). At its core lies the use of advanced digital technologies to facilitate the transformation to a circular economy (Ortega-Gras et al., 2021).

However, while the "what" of ESG integration is clear, the "how" is difficult in practice. The central challenge facing ESG management today is how to create a new framework that shifts the reliance on retrospective and often inconsistent ESG disclosures to credible, forward-looking strategic decision-making (Chopra et al., 2024). Managers generally lack quantitative tools that can reliably predict the aggregate future impact of today's capital decisions, leading to a significant "data-to-decision" gap (INREV, 2025). This is essentially a Strategic Foresight dilemma and reflects the common dilemma of companies building and adapting their organisational capabilities to meet grand challenges in a rapidly changing environment.

1.2 Literature review

ESG integration in the real estate industry faces multiple challenges. First, data quality and comparability are ongoing issues. While different rating agencies and reporting frameworks (e.g., GRESB, GRI) provide structure (Anders et al., 2025), differences in their methodologies lead to inconsistent ratings, making cross-asset and cross-market comparisons difficult (Gleeson-White, 2014; Chatterji et al., 2016; Berg et al., 2022). Second, the risk of "greenwashing" seriously erodes the trust of investors and stakeholders (Lashitew, 2021; Li et al., 2023; Mehmeti et al., 2024; Poiriazi et al., 2025). Under increasing pressure to report environmental impacts, some companies selectively disclose relatively benign impacts, creating an impression of transparency while obscuring their actual performance (Marquis et al., 2016). Companies may exaggerate their environmental performance by issuing vague or misleading statements, while the lack of verifiable forward-looking data makes these statements difficult to falsify (Yu et al., 2020; Pigatto et al., 2023; Dorfleitner & Utz, 2024; Jurgelāne-Kaldava et al., 2024). Finally, traditional ESG analysis is often static and isolated. Instead of accepting multiple perspectives, it often becomes one-sided and dominated by business case logic (Roszkowska-Menkes et al., 2024). It fails to fully capture the complex interactions between the three pillars of E, S, and G, and cannot provide adequate support for dynamic, long-term capital allocation decisions (INREV, 2025).

The "twin transformation" theory provides a conceptual framework for addressing the above challenges. The theory believes that digital transformation and green transformation are mutually synergistic and mutually reinforcing (Baumgartner et al., 2025; Schallmo et al., 2025). Digital technologies, particularly artificial intelligence (AI), the Internet of Things (IoT), and digital twins (DT), are viewed as fundamental enablers of sustainable development (Ortega-Gras et al., 2021; Askar et al., 2024). In the built environment, DT technologies bridge the data-to-decision gap by creating dynamic virtual replicas of physical assets, allowing managers to simulate, predict, and optimise in a risk-free environment (Kang & Mo et al., 2024; Ohueri et al., 2024).

Moreover, there are considerations related to human decision-making beyond the ESG framework. Human values have been shown to play a pivotal role in shaping decision-making across contexts, influencing individuals' willingness to take risks, adopt new behaviours, and engage in practices with broad societal implications. For example, a study in Latvia identified distinct value profiles between taxpayers and tax evaders: individuals who prioritised self-centred or ambitious values were significantly more inclined to evade taxes (a

grey economy behaviour), whereas those endorsing values like inner harmony and tradition tended to view tax-paying as the socially proper course. Notably, the latter group also exhibited more sustainable consumer tendencies—over half reported choosing eco-friendly products, even at a premium price (53%, compared to 45% in the general population). This finding suggests that pro-social and transcendent values correlate with responsible, sustainability-oriented behaviours (Kaže, Škapars & Bolinskis, 2011). It highlights how underlying values can drive choices that impact social and environmental outcomes. Similarly, in the realm of regional development, aligning services with human values has been found to be critical (Kazieva, Große & Larsson, 2024).

Extending these insights to technological innovation, it becomes evident that the adoption of tools such as digital twins for sustainability-oriented projects is not determined solely by technical capability. Digital twin (DT) adoption and sustainable innovation may hinge on value alignment, user well-being, and cultural fit. Values constitute the “dominating force” behind human motivation; thus, an innovation that resonates with stakeholders’ core values is more likely to be accepted and used effectively, whereas one that conflicts with or ignores those values may face resistance regardless of its touted benefits. In practice, this means that even a highly sophisticated DT solution must align with the beliefs and needs of its end-users and the broader community. If a community strongly values tradition or social cohesion, for example, they might be hesitant to embrace a new digital system unless it is framed and implemented in a way that respects and supports those values. Prior literature supports the importance of such alignment: understanding the value dispositions of target user groups allows for tailored communication and implementation strategies. Interventions (e.g., campaigns against tax evasion) are more effective when framed in terms of the values important to the audience, rather than purely utilitarian arguments. Thus, promoting digital twin initiatives in a manner that emphasises their consonance with local values (such as community empowerment, environmental stewardship, or economic security, depending on context) could be pivotal for encouraging uptake. Ultimately, bridging the gap between technical solutions and human values is essential for technology adoption that genuinely contributes to long-term well-being and sustainability. This is well-observed if values are studied by novel tools that exclude biases, e.g. image-based methods that are assisted by machine-learning (Kaže et al., 2022), which implicitly suggest that integrating advanced value assessment methods, like image-based tools, into the innovation process offers a promising pathway to ensure that digital twin technologies and other sustainable innovations resonate with end-users’ values, thereby enhancing adoption and positive impact.

Building on these human-centric considerations, organisational readiness for digital transformation emerges as another critical enabler of sustainability-oriented innovation, including DT. It has been illustrated that leveraging e-environment tools (i.e., Internet-based platforms) yields significant benefits for sustainable business development. The study also found that many companies remain at only an initial stage of mastering such digital tools, underutilising even basic resources. This gap in digital literacy and e-readiness suggests that without a baseline of technological competence and awareness, firms may struggle to realise the full potential of advanced digital innovations (such as digital twin (DT) solutions) in driving sustainable development. In other words, organisational digital maturity – including up-to-date e-environment strategies – is a foundational precondition for translating technical capabilities into successful sustainability-oriented innovation.

Similarly, gaps in sustainability awareness among stakeholders can undermine the impact of digital transformation initiatives. The reports on Poland, Latvia and Japan suggest that, despite broad policy efforts, encompassing all pillars of sustainability, the general public’s sustainability awareness and knowledge remain below the global average (Miszczak et al., 2024). Although gradual improvements have been observed, this persisting awareness deficit signals a risk factor that may limit stakeholder support for new technologies like DTs aimed at sustainability. These findings underscore the importance of strengthening both sustainability-oriented mindsets and digital competencies. By bridging such awareness and capability gaps, organisations create a foundation where digital transformation efforts – exemplified by DT adoption – are value-aligned and more likely to accelerate progress toward sustainable innovation and development goals.

Deep reinforcement learning (DRL), an advanced AI technology, has demonstrated significant potential in solving complex dynamic optimisation problems, such as HVAC control (Lazaridis et al., 2024; Liao et al., 2024). Compared with traditional rule-based or model-predictive control methods, DRL can autonomously learn

adaptive strategies to achieve a better balance between energy efficiency and comfort management (Chowdhury et al., 2024). However, the application of DRL also faces challenges, such as inefficient training data and trust issues in the "black box" decision-making process. Combining DRL with high-fidelity DT provides an effective path to solve these problems (Bousnina & Guerassimoff, 2024; Hagström et al., 2025).

This study is based on this series of academic backgrounds. It aims to demonstrate, through a specific case, how a framework integrating PINN, DT, and DRL can systematically address the strategic foresight problems inherent in traditional ESG management.

1.3 Research Objectives and Framework

To bridge the "data-to-decision" gap, this paper proposes and validates a dynamic ESG management framework based on Digital Twin (DT) and Deep Reinforcement Learning (DRL) utilising digital twin technology. The framework aims to transform ESG from a static compliance reporting activity to a proactive, data-driven strategic management function.

The core research question of this paper is: how can a DT framework integrated with DRL provide forward-looking and strategically valuable decision support for decarbonization investments in commercial real estate through multi-criteria scenario analysis?

To answer this question, this paper will follow the IMRAD structure:

The "Methods" section will detail our approach to constructing the DT environment, training the DRL intelligences, and designing scenario analyses for the four ECMs, as well as presenting the experimental subjects and data. The "Results" section will present the quantitative results of the scenario analysis, including a decision matrix that integrates financial, environmental, and social benefits, as well as an analysis of 3D Pareto charts and sensitivity tornado diagrams. The "Discussion" section will provide insights into the managerial and sustainability implications of these results, particularly in relation to the dynamic capabilities framework of "sense-capture-reconfigure", exploring how it can reshape ESG governance, and discussing its limitations and future research directions.

2. Methods

The methodology of this study aims to develop a "cyber-physical vision engine" capable of forward-looking decision analysis and to utilise it as an experimental platform for testing dynamic capability theory. Here we dramatically simplify the technical process, focusing instead on the management functions and the value of decision support at each stage.

2.1 Phase 1: Building a High-Fidelity Digital Twin Environment

The basis of the analysis is a high-fidelity digital twin environment for building thermodynamics. We do not use pure white-box physics models (e.g., RC models), which are challenging to capture real-world complexity and lead to model mismatches. Instead, we employ the Physics-Informed Neural Network (PINN) technique. PINN makes it possible to fit the observed data while its output must obey the laws of physics by embedding the laws of physics (thermodynamic equations) as a soft constraint in the loss function of the neural network. This ensures that our digital twins are both physically interpretable and highly compatible with real data, providing a reliable "gym" for subsequent DRLagent training (Ohueri et al., 2024; Pomè & Signorini, 2024).

The following differential equations control the thermal dynamics of the building:

$$C, \frac{dT_{in}}{dt} = \frac{1}{R} (T_{out} - T_{in}) - \eta_u P_{HVAC} + Q_{int}$$

where C is thermal capacitance, R is thermal resistance, T_{in}/T_{out} are indoor/outdoor temperatures, P_{HVAC} is HVAC power, η_u is a utility factor, and Q_{int} is internal heat gain.

The PINN is trained to minimise a composite loss function, $\mathcal{L}$, which includes both the data-fit error ($\mathcal{L}_{data}$) and a penalty for violating the physical law, represented by the physics residual, $\mathcal{R}$:

$$\mathcal{R} = C\dot{T}_{in} - \frac{1}{R}(T_{out} - T_{in}) + \eta_u P_{HVAC} - Q_{int} \quad , \quad \mathcal{L} = \mathcal{L}_{data} + \lambda \|\mathcal{R}\|_2^2$$

Here, λ is a hyperparameter from $1 \rightarrow 0.01$, with a gradual decay. By penalising deviations from the physical equation, the network is forced to learn physically meaningful and generalizable parameters (R , C , η_u), creating a robust knowledge base for subsequent transfer.

From a management perspective, the core of this phase is to provide companies with a low-cost, risk-free “strategy sandbox”. On this sandbox, managers can simulate the long-term consequences of different capital investment decisions, thus making invisible future risks (e.g., stranded assets) and opportunities (e.g., energy-saving potential) visible and quantifiable. This corresponds directly to the Dynamic Capability Theory’s “Sensing” capability - the ability to recognise and assess opportunities and threats in the external environment.

2.1.2 Phase 2: Training and Evolving the DRL agent

We mapped the calibrated digital twin model to a building with only static metadata by transfer learning to map the dynamic laws to a building with only static metadata. We ultimately encapsulated the validated digital twin environment in combination with DRL into an OpenAI Gym-compliant BuildingEnv class, which is used as a high-fidelity simulation environment to train the Deep Reinforcement Learning (DRL) agent. To apply reinforcement learning, the building control problem is formalized as a Markov Decision Process (MDP), a mathematical framework for modeling decisions in environments where outcomes are partially stochastic and partially under the control of the decision maker. Its core components define the MDP:

State(s_t): agent-observable information, initially [indoor temperature, outdoor temperature, time vector].

Action(a_t): discrete control actions that the agent can take, i.e., nine different HVAC temperature setpoints.

Reward(rt): The objective function that guides the agent’s learning is to minimise the weighted sum of energy consumption, comfort deviation, and control action changes. Our reward function is designed as a multi-objective cost function to be minimised, explicitly balancing environmental, economic, and social goals:

$$r_t = -(c_e P_t + c_d \max(0, P_t - P_{thr}) + c_c |T_{in} - T_{set}|)$$

where P_t is the energy consumption, T_{in} is the actual indoor temperature, and T_{set} is the chosen setpoint. The weighting coefficients c_e , c_d , and c_c allow for tuning the relative importance of each objective.

Subsequently, we used the Deep Q-Network (DQN) algorithm, a classical value function estimation algorithm in DRL for discrete action space problems (Chowdhury et al., 2024; Lazaridis et al., 2024; Liao et al., 2024). More importantly, to address the data asymmetry problem (i.e., a few buildings have detailed data, while most have sparse data) common in real estate portfolios, we employ a transfer learning approach. This approach allows us to extend the dynamics and control strategies learned from a single data-rich “source building” to a data-sparse “target building” at a very low marginal cost. This significantly enhances the scalability and real-world application value of the framework, addressing the major management challenge of scaling case-by-case insights into comprehensive portfolio strategies. This phase shifts from reactive forecasting to proactive optimisation, aimed at discovering the best operational strategies that can directly improve the sustainable performance of an asset, which constitutes an intelligent “refactoring” of existing operational routines.

2.1.3 Stage 3: Multi-criteria scenario analysis design

This is the core methodological phase of this study. We modelled and evaluated four hypothetical scenarios using the framework of Multi-Criteria Decision Analysis (MCDA) (Deda et al., 2025; Gaievskiy et al., 2025; Grondin et al., 2025), a structured decision support tool for evaluating alternatives between multiple, often conflicting, criteria (Mecca, 2023; Gaievskiy et al., 2025).

The four hypothetical scenarios are as follows:

1. DRL Control: Our final trained high-performance DRL agent is applied to the existing building, and its performance serves as a benchmark against which all hardware retrofit measures are compared.
2. LED Retrofit: Based on DRL Control, we simulate the effect of replacing conventional lighting with high-efficiency LED lighting systems. The benefits are split into two components:
Direct Lighting Savings: Engineering estimate based on industry standard (10.5 kWh/m²/year).

Indirect HVAC Savings: Based on the industry standard engineering methodology of “for every 3 kWh of lighting savings, an additional 1 kWh of air conditioning savings”.

3. Chiller Upgrade (HVAC COP Upgrade): Simulates the effect of replacing a high-efficiency chiller by increasing the HVAC efficiency parameter η by 20% in a simulated environment, based on DRL control.

4. Solar PV: Based on DRL control, analyse the effect of installing 50kWp PV panels to offset grid electricity consumption. The annual energy production is calculated using industry-standard engineering calculations based on annual average peak sunshine hours (PSH) and system performance ratio (PR).

Evaluation criteria include: (1) Financial metrics: annual electricity savings (GWh), estimated total investment (SGD), simple payback (years); (2) Environmental indicators: annual carbon emission reduction (t-CO₂); (3) Social indicator: annual social benefit (SGD), calculated by annual carbon emission reduction $\times$ social cost of carbon (SCC). We use a widely cited estimate based on international studies, which is 243.20 SGD/tCO₂, derived from an interagency working group led by the U.S. Environmental Protection Agency (EPA). According to the EPA’s latest report, its recommended central estimate (at a 3% discount rate) is about \$190/tCO₂ (in 2022 dollars) (U.S. Environmental Protection Agency, 2022; Howard & Sylvan, 2024; Ashenfarb & Kotchen, 2025; Prest & Rennert, 2025).

All energy consumption results based on short-term simulations (1461 hours) were calibrated using an annualization factor ($8760/1461 \approx 6.0$) to ensure that all analyses were performed at an annual scale. This process embodies the complete closed-loop application of digital twin technology in building energy management, from understanding the current situation to predicting the future, optimising operations, and assisting in decision-making, thereby giving it the attributes of being data-driven, seamlessly interactive, and featuring closed-loop feedback.

2.2 Data and Cases

To validate the utility and effectiveness of the framework, this study applies it to a real dataset in Singapore. Singapore presents a unique and compelling context for this research. As a densely populated, highly urbanised island nation, it faces significant pressure to manage its resources efficiently and mitigate its environmental impact. In response, the government has launched the Singapore Green Plan 2030, a comprehensive national agenda that outlines ambitious targets for sustainable development, including stringent goals for greening the building stock. This makes Singapore a "living laboratory" for testing and deploying innovative solutions that aim to achieve urban sustainability.

This study utilises a rich dataset from the Building and Construction Authority (BCA), Energy Market Authority (EMA), and Meteorological Service Singapore (MSS), covering 564 commercial buildings in Singapore from 2017 to 2020, including office buildings, retail spaces, and hotels. A rich dataset from BCA, Energy Market Authority (EMA) and Meteorological Service Singapore (MSS), covering 564 commercial buildings in Singapore from 2017 to 2020, including offices, retail spaces and hotels. The data sources are diverse, encompassing both static metadata and dynamic time-series data. Among them, Harbourfront Centre is the benchmark building, and its highly granular data can be used to build benchmarking models and generalise insights from a single source asset through migration learning to create physically-based energy performance benchmarks for each of the remaining buildings. This data structure (one building with exhaustive data and the remaining buildings with sparse data) perfectly models the real-world data asymmetry challenge that the framework aims to address. Table 1 provides the architecture of the available data. Each data point is not just a technical input, but a key indicator for sustainability assessment.

Table 1. Data Schema and Availability Across Building Portfolio

Category	Field Name	Description	Data Availability	Time Granularity
Universal Dynamic Data	Outdoor Temperature (Tout)	Ambient air temperature	All 564 Buildings	Daily (2017–2020)
	Grid Emission Factor (GEF)	Carbon intensity of the electricity grid	All 564 Buildings	Daily (2017–2020)
Source-Specific Dynamic Data	Electricity Tariff	Cost of electricity	All 564 Buildings	Daily (2017–2020)
	Cooling Electrical Power (PHVAC)	Power consumed by the HVAC system	Source Building	Daily (2017–2020)
Universal Static Metadata	Indoor Temperature (Tin)	Average internal building temperature	Source Building	Daily (2017–2020)
	Green Mark Rating/Year	Building sustainability certification	All 564 Buildings	Single Point
	Gross Floor Area (GFA)	Total floor area of the building	All 564 Buildings	Single Point
	% Air-Conditioned Area (%AC)	Percentage of GFA that is cooled	All 564 Buildings	Single Point
	LED Penetration (%LED)	Percentage of lighting that is LED	All 564 Buildings	Single Point
	Chiller COP	Coefficient of Performance of the chiller plant	All 564 Buildings	Single Point
	Occupancy	Typical occupancy level or pattern	All 564 Buildings	Single Point
	PV Flag	Presence of photovoltaic systems	All 564 Buildings	Single Point
	System Type	Type of HVAC system installed	All 564 Buildings	Single Point
	Geographical coordinates	latitude/longitude	530 Building	Single Point
	Building Size	Large or Small	532 Building	Single Point
	Main building functions	Office Hotel Retail	522 Building	Single Point

Source: Singapore BCA, EMA, & MSS

In terms of experimental setup, this study uses data from 2017 to 2019 for model training. We selected data from a normal year (2018) and an abnormal epidemic year (2020) as a cross-test set to evaluate the final performance and generalisation ability of the model. This design was intentional. Tools used for long-term sustainability planning and investment must be robust and reliable. We explicitly stress-tested the resilience of the framework by testing it against the “black swan” event of the COVID-19 outbreak, which led to significant conceptual drift in energy use patterns. A model that can maintain predictive accuracy under such volatile conditions will be even more trustworthy as a basis for making multimillion-dollar investment decisions to achieve long-term sustainability goals.

Table 2. Baseline model performance assessment

Model	RMSE(kWh · m – 2 · yr)	R ²
Persistence model	67.59	0.8680
Mean model	74.68	0.8388
Differential persistence model	79.57	0.8170

We then built a simple baseline model for the 522 heterogeneous data, and the results, as shown in Table 2, show that the simplest persistence model (i.e., predicting that the following year's EUI is equal to the previous year's EUI) performs the best, achieving surprisingly high performance on the test set. Its Root Mean Square Error (RMSE) is 67.59 kWh-m⁻²-yr, and the coefficient of determination (R²) is as high as 0.8680.

In this study, HarbourFront Centre in Singapore is selected as the source domain building. At the same time, based on the statistical analysis of the data showed that 2020 was an abnormal data year, the experimental scheme of Benchmark HarbourFront Centr digital twin was trained on the existing data with a strict time segmentation, using the 2017-2019 data as the training set, the 2018-Q1 and 2020 datasets were normalized to validate the epidemic validation, to realize the normalized + epidemic dual validation method.

The final Benchmark parameters obtained are $R = 5.02^{\circ}\text{C} - \text{day/kWh}$, $C = 2.04\text{kWh}/^{\circ}\text{C}$, $\eta=0.704$ (see Table 3).

Table 3. Benchmark parameters

Parameter	Numeric value	Typical range	Evaluate
R	$5.02^{\circ}\text{C} \cdot \text{day/kWh}$	2 – 10	Normal
C	$2.04\text{kWh}/^{\circ}\text{C}$	1 – 5	Normal
η	0.704	0.6 – 0.9	Normal

Meanwhile, the normality validation, epidemic validation, and the training set are all in line with the engineering accuracy of the grey-box model.

3. Results

Based on the above data, we validated the model and trained a practical intelligence, which was applied to scenario simulation and analysis. We then aggregated the core quantitative results into a comprehensive investment decision and policy priority matrix, visualised and presented through 3D Pareto plots and sensitivity Tornado plots.

3.1 DRL agent learning results and model validation

Figure 1 illustrates the reward performance of the DRL agent over 500 rounds, from which we can see that at the beginning of training (Episode 10), the average score was -2554. As the training progressed, the average score steadily increased. By the end of training (Episode 500), the average score reaches -1171. The continuous increase in the score clearly indicates that the DRL agent is learning effectively. It is gradually finding control strategies that reduce the total cost (energy + discomfort + control changes) by interacting with the environment (Figure 1).

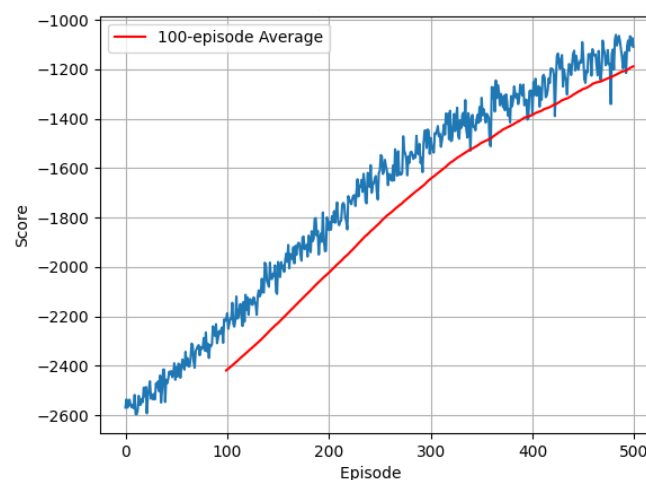


Figure 1. Changes in total rewards for intelligent body learning

After a series of systematic and targeted iterative optimisations, a high-performance DRL agent was successfully obtained. A 47.14% HVAC control energy saving rate was achieved in a trusted digital twin environment calibrated by a physical model, providing solid data support for its application in real buildings.

More importantly, this significant energy saving result was achieved under the premise of strictly ensuring the comfort of indoor occupants, and the total comfort deviation was controlled at an extremely low level (29.13 °C·h) (see Table 4).

Table 4. Performance comparison of DRL agent and baseline policy

Metric	DRL Agent	Baseline (24°C)
Total energy (kWh)	707.45	1338.42
Total Comfort Deviation (°C·h)	29.13	0.00
Energy savings	47.14%	/
Total Reward	-860.54	1338.42
Action Change Cost	24.75	0.00

It can be seen that the agent has excellent predictive ability and balanced decision-making ability, which fully demonstrates the great potential and value of this technical route in the field of sustainable real estate management.

3.2 Integrated Decision and Policy Prioritisation Matrix

This study assumes a total annual energy consumption of 31,307.84 megawatt-hours (MWh) for the base building in FY2020 as the baseline value for the subsequent calculation of the total energy saving rate, assuming a total gross floor area (GFA) of 169,727 square meters (m²), and sets the Social Cost of Carbon (SCC) at SGD 243.20 per ton of CO₂ (SGD/tCO₂) (Table 5).

Table 5. TOPSIS Energy Saving Potential Ranking Table

ECM Scenarios	Building-wide Annual Energy Savings (%)	Building-wide Annual Energy Savings (GWh)	Building-wide Annual Carbon Reductions (t-CO ₂)	Estimated Total Investment (SGD)	Building-wide Simple Payback Cycle (Years)	Societal Benefits (via SCC, SGD)	Policy Prioritisation (TOPSIS)
DRL Control Strategy	1.23%	0.39	157.51	~0 (software cost)	< 1	38,300	Base
Install PV panels	0.21%	0.07	26.74	75,000	3.83	6,503	High
LED lighting retrofit	7.59%	2.38	967.10	7,637,715	10.77	235,213	High
Increase chiller COP	< 0.01%	< 0.001	0.23	5,100,000	29,806.11	56	Low

The energy savings for “Installation of Photovoltaic Panels”, “LED Lighting Retrofit”, and “Increase in Chiller COP” in Table 5 represent incremental benefits resulting from the implementation of the “DRL Control Strategy”. DRL control strategy".

3.3 Visualisation and analysis

3.3.1 3D Pareto chart: finding the optimal decision frontier

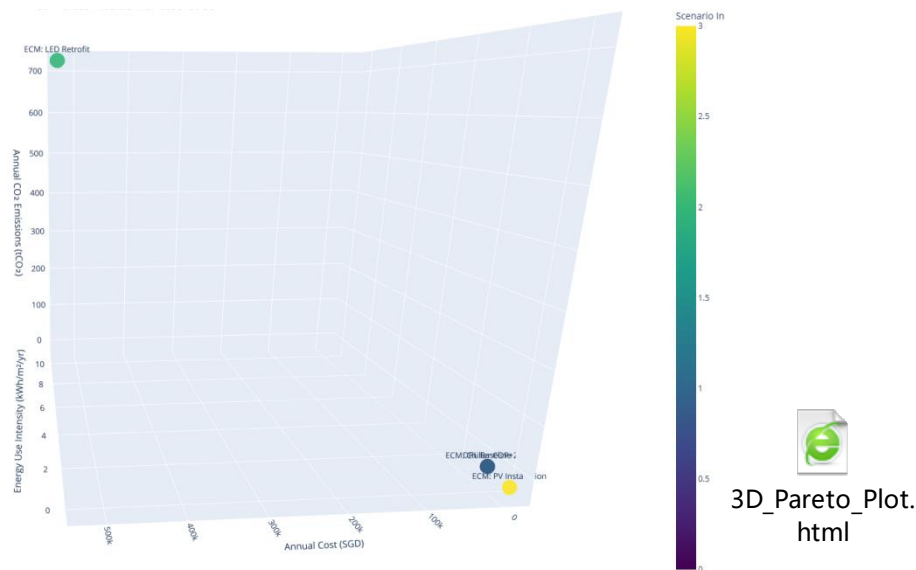


Figure 2. 3D Pareto chart

The 3D Pareto diagram visualises the combined performance of the scenarios in three dimensions: energy intensity (EUI), annualised costs, and annualised carbon emissions. The ideal scenario is as close as possible to the origin of the coordinate system (see Figure 2 above).

In the decision analysis of the scenarios, the option “Increase chiller COP” almost coincides with the DRL Benchmark, indicating that after Deep Reinforcement Learning (DRL) optimisation, the marginal benefit is almost zero. The marginal benefit is almost zero, so other, better options have fully outperformed it and can be considered an ineffective option with an insufficient return on investment.

Meanwhile, LED Retrofit and Photovoltaic Installation constitute the Pareto-optimal frontier for decision making, implying that there is no absolute advantage or disadvantage in all evaluation indicators. There is no absolute advantage or disadvantage, but rather a trade-off between the two - the former being the most significant in terms of reducing overall energy consumption, and the latter having a greater advantage in terms of speed of financial return.

3.3.2 Sensitivity Tornado diagrams: identifying key drivers

The sensitivity analysis quantifies the influence of key building parameters on the total energy consumption through Tornado plots, with Internal Heat Gain identified as the most sensitive leveraged variable, contributing most significantly to the energy consumption of the HVAC system; this finding explains the significant indirect energy savings from the LED retrofit in terms of reducing the heat dissipation of the lighting from the physical mechanism.

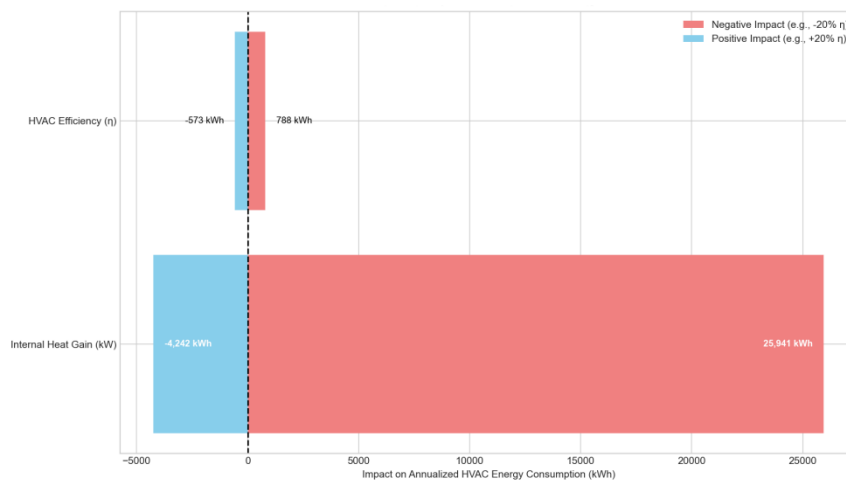


Figure 3. Sensitivity Analysis Tornado Plot

In contrast, the energy efficiency (η) The performance of the HVAC equipment also shows some sensitivity (Figure 3). However, its influence is significantly smaller than that of the internal heat source, which further confirms that there is limited scope for additional energy savings by simply improving the efficiency of the hardware itself after Deep Reinforcement Learning (DRL) optimisation has already achieved an increase in operational efficiency.

4. Discussion

The findings of this study not only provide a basis for specific investment decisions but, more importantly, provide profound inspiration for the ESG management paradigm and sustainable development strategy of the real estate industry. We will systematically explain how this framework transforms ESG from a compliance burden into a dynamic governance capability that creates value, centring on the "sense-capture-reconstruct" syllogism of dynamic capability theory.

4.1 Sensing: Using digital twins to gain insight into future risks and opportunities

The dynamic capability theory defines "sensing" as the ability to identify and assess opportunities and threats in the external environment. In traditional ESG management, this "sensing" ability is severely limited due to the lack of forward-looking tools and metrics. Our framework gives managers a digital "sensing" ability through a simulation environment based on digital twins.

It allows managers to conduct "what-if" analysis of different energy-saving investment measures (ECMs) in a risk-free virtual space, thereby "sensing" the comprehensive impact of different capital decisions on dimensions such as energy, cost, carbon emissions, and comfort in the future. For example, managers can foresee that a costly chiller upgrade will become an investment with little return after the AI agent optimises operations, effectively avoiding the risk of "stranded assets" that may result from climate transition. This capability enables companies to go beyond the limitations of historical data and gain insight into the future state of their assets under various strategic paths, thereby actively shaping their environment rather than passively adapting to it.

4.2 Seizing: Seizing Value through a Data-Driven Framework

The "seizing" capability refers to the action of mobilising and allocating resources to capitalise on opportunities and create value. If "perception" is seeing the future, then "seizing" is making choices to achieve the optimal future. The multi-criteria decision analysis (MCDA), Pareto frontier diagrams, and TOPSIS rankings in this article are the decision-making mechanisms for "capturing" value.

They provide a structured, data-driven basis for capital allocation, helping managers make trade-offs between multiple (sometimes conflicting) goals. For example, based on the analysis results in Table 5 and Figure 2,

decision makers can clearly see that although the total energy saving effect of the photovoltaic project is limited, it has the fastest financial return (3.83 years' payback period). In comparison, the LED transformation project has a significant initial investment and a long payback period (10.77 years). However, its total energy saving potential and social benefits (measured by SCC) are the highest among all options. This quantitative trade-off analysis enables managers to effectively "orchestrate" corporate resources and make the most favourable investment decisions based on their own strategic priorities (for example, whether to prioritise short-term cash flow or long-term social impact).

4.3 Transforming: Reinventing assets and routines for long-term resilience

The ability to "transform" refers to the ability to continuously update and transform the organisation's asset base and operating routines to maintain competitiveness. This framework promotes "transforming" at two levels.

At the micro level, the AI agent itself is a "reconstruction" of operating routines. It replaces the traditional, static rule-based HVAC control model with an adaptive, continuously learning dynamic optimisation model, which is a manifestation of organisational learning and adaptation at the operational level. At the macro level, the entire framework prompts companies to "reconstruct" their capital investment strategies. It encourages companies to shift from a logic of solely pursuing short-term financial returns to a more resilient, long-term value creation logic based on ESG multi-dimensional goals. For example, by introducing the "social cost of carbon" (SCC) and incorporating social benefits into the TOPSIS ranking, the framework guides decision makers to internalise externalities, which is a key step in "reconstructing" sustainable business models.

4.4 Transforming ESG from compliance reporting to dynamic governance

The core contribution of the DT-DRL framework proposed in this study is to transform ESG management from a passive, retrospective reporting activity to a proactive, forward-looking dynamic governance mechanism.

1) Governance "E" Dimension: Verifiable Decarbonization Path: Under increasing pressure to report environmental impacts, some companies selectively disclose relatively benign impacts to create the impression of transparency while hiding their actual performance. Traditional ESG reporting is often criticised for "greenwashing" due to its static and retrospective nature (Marquis et al., 2016; Poiriazzi et al., 2025). Our framework offers a scientific and auditable methodology for ex-ante assessment and validation of decarbonization pathways, directly responding to market demand for transparency and credibility (Cojoianu et al., 2024). It enables companies to confidently set and communicate their Science-Based Targets (SBTs) (Pinkse et al., 2023).

2) Governance of the 'S' dimension: quantifying human-centred values: The reward function of the DRL agent is a concrete operational tool for realising the governance of the social dimension. It transforms occupant comfort, a key social (S) metric, from a vague concept into a quantifiable, optimizable, and trade-offable operational parameter. This enables managers to explicitly manage and safeguard occupant well-being while pursuing cost-effectiveness, thereby enhancing the social value of the asset (American Assets Trust, Inc., 2024; Sekisui House Reit, Inc., 2024).

3) Governance "G" Dimension: Managing Stranded Asset Risks: Our analysis clearly identifies "upgrading chiller COP" as an ineffective investment. This is the core value of the framework as a risk management tool - avoiding Stranded Asset Risk due to the climate transition (Allianz, 2025; European Commission, 2025). Under increasingly stringent building energy efficiency regulations (e.g., EU EPBD) (European Commission, 2024; Shahid et al., 2024), inefficient assets are at significant risk of depreciation. Our framework improves the performance of existing assets at a fraction of the cost through "software over hardware" optimisation, effectively avoiding significant capital mismatches that could quickly "run aground". This provides strong decision support for boards and management to fulfil their fiduciary responsibilities in an era of climate risk (ICG, 2025; Lazard Asset Management, 2024).

4.5 The "social cost of carbon" and policy priorities

To elevate the analysis of this study to a strategic level, we introduced the Social Cost of Carbon (SCC) as a measurement tool, which is defined as the long-term economic loss to society per unit of CO₂ emissions (Ashenfarb & Kotchen, 2025; Howard & Sylvan, 2024; Prest & Rennert, 2025). With the help of the SCC value (243.20 SGD/tCO₂), the corresponding societal benefit (SGD) can be calculated by multiplying the annual carbon emission reduction (tons of CO₂) of each measure by this cost factor. On this basis, we adopted the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method to rank the policy options

comprehensively. This method measures the relationship between each option and the “optimal ideal solution” (i.e., the solution with the shortest payback period and the best social benefits). The method prioritises the policy options by measuring their distance from the “optimal ideal solution”, i.e. the one with the shortest payback period and the highest social benefits. The results show that PV module installation is closest to the “shortest payback” ideal, and LED lighting retrofit is closest to the “highest social benefit” ideal, thus both are rated as “high” priority; in contrast, LED lighting retrofits are rated as ‘high’ priority; in contrast, LED lighting retrofits are rated as “high” priority. “In contrast, upgrading the chiller COP was the furthest away from the ideal solution in terms of both payback period and social benefits, and was therefore rated as a “low” priority.

4.6 Managerial and Policy Implications

The results of this study provide targeted strategic recommendations for various types of decision-makers. For private sector investors, the deployment of intelligent control technologies such as Deep Reinforcement Learning (DRL) should be prioritized as a first investment area, as it maximizes the operational performance of existing assets at a low marginal cost; based on this, it is recommended to prioritize the installation of photovoltaic (PV) modules that have a short payback period and a quick payback in cash flow; In contrast, measures such as LED lighting retrofits, which have significant social benefits but relatively long private payback periods, should be incorporated into medium- and long-term capital renewal planning. On this basis, it is recommended that priority be given to PV module installation projects with short payback periods and quick cash flow returns. In contrast, measures with relatively long private payback periods despite their significant social benefits, such as LED lighting retrofits, should be included in medium- and long-term capital renewal planning and various external incentives should be actively pursued to enhance their investment attractiveness. For public policymakers, this study identifies a gap between the high social benefits and long private payback periods for LED lighting retrofits, providing an ideal entry point for incentive policies. Through mechanisms such as green building subsidies and tax credits, this benefit-payback gap can be effectively bridged to promote socially optimal solutions. At the same time, the promotion of Just Transition should be at the core of the policy, i.e., ensuring a fair distribution of costs and benefits during the promotion of energy efficiency retrofits to avoid disproportionate burdens on low-income groups and SMEs (Hughes & Hoffmann, 2020; Johnston, 2025), e.g., by setting up a special fund to support In addition, the government should strongly encourage enterprises to invest in software-defined technologies such as DRL intelligent control through financial and policy support, as they are one of the cost-effective paths to achieve the national goal of “carbon neutrality”.

4.7 Implications for organisational learning and digital transformation

The contribution of this study extends beyond the expansion of dynamic capability theory, also providing important implications for digital transformation and organisational learning within organisations. Digital transformation is not simply a technological integration, but a profound organisational learning process; in this process, the digital twin-deep reinforcement learning framework proposed in this study can be regarded as an “organisational learning engine”. First, by viewing building operations as complex adaptive systems, the framework guides managers to adopt systematic thinking and gain a deep understanding of the mutual coupling and feedback mechanisms between subsystems, such as lighting and HVAC, thereby achieving overall optimal decision-making under multi-objective trade-offs. Second, digital twins provide managers with a low-risk, high-fidelity virtual experimental field, encouraging them to quickly iterate and verify cutting-edge or even disruptive operational strategies in a simulated environment, thereby cultivating an innovative culture that advocates experimentation, tolerance and learning from failure. Ultimately, the framework quantifies the typically abstract ESG goals into measurable performance indicators. It combines deep reinforcement learning to generate optimal strategies in real-time, fundamentally promoting the decision-making paradigm from experience-driven to data-driven and evidence-based. This series of mechanisms jointly promotes the learning ability, innovative mindset and data culture required for the digital transformation of organisations, and provides a reference path and theoretical support for the digital practices of the construction industry and broader enterprises.

4.8 Limitations and directions for future research

Although this study has achieved significant results in operational carbon optimisation, several limitations still need to be addressed and improved upon in future studies. First, this study primarily focuses on operational carbon emissions. In contrast, the proportion of Embodied Carbon (EC) in total life cycle carbon emissions is becoming increasingly prominent with the continuous improvement of building energy efficiency (Terán-

Cuadrado et al., 2024). Therefore, subsequent studies should incorporate Life Cycle Assessment (LCA) data into the Digital Twin (DT) framework to achieve comprehensive optimisation of carbon emissions over the whole life cycle of a building. Additionally, this study focuses on a single building as its object of analysis. In contrast, in practical applications, decision-makers often need to manage and optimise their entire real estate portfolio dynamically. Future work should integrate the DTDRL method more deeply with spatio-temporal models, such as the SpatioTemporal Graph Convolutional Network (ST-GCN), to achieve Environmental, Social, and Governance (ESG) objectives at a more macro scale.

On the other hand, deep reinforcement learning models are often regarded as “black boxes” in the control strategy generation process, and their decision logic lacks transparency, which limits their generalisation to high-risk financial and operational scenarios (Haghighat et al., 2025; ITSM GOAL, 2025; Perera et al., 2025). To this end, there is an urgent need for future research to integrate Explainable AI (XAI) techniques to reveal the core decision rules underlying the DRL Agent's energy consumption control process in order to build a foundation of trust, facilitate human-machine collaboration, and meet the increasingly stringent requirements for regulatory interpretability (Lakshmi et al., 2024; Siu et al., 2025).

Conclusions

In today's property and sustainability management, digital twins combined with deep reinforcement learning (DRL) methods represent a game-changer that can dramatically change the way we manage energy consumption, capital expenditures, and achieve ESG goals. The results of this study demonstrate that the integration of digital twins and intelligent algorithms opens up a new level of organisational management, transforming it from a traditional reactive model to a proactive, dynamic, and data-driven process:

1. Digital twins as a driver of organisational learning and decision making. One of the key advances is that digital twins provide managers with a virtual environment in which to simulate and evaluate the impact of various investment and operational decisions without risking tangible assets. This allows them to “feel” the future, predicting the impact of energy conservation and decarbonization measures on energy consumption, costs, carbon emissions, and user comfort. This capability fundamentally changes the role of the manager: from an executor of prescriptions, he or she becomes an active strategic player, capable of systematically analysing complex relationships and trade-offs between various performance indicators. Virtual experiments and scenario modelling stimulate innovative thinking and a culture of learning from mistakes, which contributes to the development of adaptability and resilience of the organisation in a rapidly changing external environment.
2. Deep reinforcement learning (DRL) as a tool for improving operational efficiency. The use of DRL enables you to continuously optimise the management of HVAC systems and other energy-intensive building subsystems, adapting to changing operating conditions. This increases operational efficiency without the need for large capital expenditures, which is especially important in conditions of limited resources and high sustainability requirements. The integration of DRL with digital twins creates a dynamic management model that not only enhances the current state of assets but also lays the groundwork for the long-term transformation of business models. This approach facilitates the transition from short-term financial return maximisation to multidimensional cost management, taking into account environmental, social, and governance factors.
3. Capital Investment Management: Trade-offs and Priorities Based on Data. An important element of the study is the use of multi-criteria analysis (MCA), specifically Pareto and TOPSIS methods, to develop sound investment priorities. Based on a quantitative assessment of the trade-offs between payback period, energy savings and the social cost of carbon (SCC), managers receive structured recommendations for capital allocation. For example, photovoltaic module installation projects demonstrate a quick payback and high financial attractiveness, which makes them a priority for short-term investments. At the same time, LED lighting retrofits, despite a more extended payback period, provide significant social and environmental benefits, which justify their inclusion in medium- and long-term strategic planning. This approach facilitates the transition from intuitive or one-sided decisions to transparent and informed investment management, taking into account sustainability - a key challenge for modern management.

4. Risk management and prevention of ineffective investments. The results show that investments in refrigeration equipment modernisation following the application of DRL optimisation are ineffective in terms of both ROI and social benefits. This highlights the importance of using digital twins and intelligent models to identify and prevent the risk of “stranded assets”, especially in the context of increasing climate regulation and stricter regulations. Thus, digital technologies and advanced analytics become integral tools of the fiduciary duties of managers and boards of directors, helping to minimise financial and environmental risks.

5. Strategic importance for ESG and digital transformation. A systematic approach implemented through digital twins and DRLs facilitates the transformation of ESG management from static and retrospective reporting to a dynamic management function. This allows not only for measuring and controlling environmental indicators, but also for quantitatively integrating social and management parameters into the decision-making process. Of particular importance is the translation of social value, for example, the comfort of residents, from an abstract concept into a measurable operational parameter, which makes it possible to purposefully manage the social component and create additional value for the business. This integrated approach fosters organisational learning, innovation, and a data-driven culture, which forms the foundation for sustainable digital transformation and long-term competitiveness within organisations.

Limitations and Future Research

Despite the successes, the current research is limited by its narrow focus on operational emissions and the analysis of individual buildings. Future work requires expanding the models to account for the carbon footprint throughout the lifecycle and scaling the solutions to a portfolio of buildings. Additionally, the development of explainable XAI methods to enhance transparency and trust in the decisions made by DRL agents is a crucial direction that will facilitate the integration of intelligent systems in high-risk and regulated areas.

Digital twins combined with deep reinforcement learning open new horizons for building management and sustainability. They enable managers to make informed, balanced decisions, optimise resource use, and mitigate risks, while fostering a culture of continuous learning and innovation. This synergistic approach is becoming a key driver of digital transformation, ensuring the long-term resilience of organisations in the face of global climate and ESG challenges.

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