Bridging the Gap: AI-Driven Generative Design for Sustainable Learning Environments and Behavioral Transformation

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Abstract: Urban buildings account for 40% of global energy consumption, yet conventional sustainable design neglects both occupant behavior and the educational potential of the built environment. This study operationalizes the convergence of Artificial Intelligence (AI), Human-Computer Interaction (HCI), and Educational Engineering to address this dual gap. We present EcoDesign-GAN, a generative adversarial network integrated with reinforcement learning, to optimize residential and educational spatial layouts for simultaneous energy efficiency and the facilitation of informal sustainability learning. Using 5,000 urban unit layouts across five global cities for training, and high-fidelity building simulation for evaluation, we examine how intelligent spatial configurations can function as a "hidden curriculum," influencing simulated energy consumption and fostering environmental literacy through experiential feedback. Simulation results demonstrate that AI-optimized designs have the potential to reduce simulated energy use by up to 25% (95% CI: 22.3%-27.7%, Cohen's d = 2.8, $p < 0.001$) and improve the adoption of sustainable behaviors and environmental awareness by 40% in controlled virtual environments, compared to matched traditional designs (n = 100 pairs). The Herfindahl-Hirschman Index (HHI = 0.15) confirms high design diversity, suggesting the GAN's capacity to generate varied learning environments adaptable to diverse cultural and pedagogical contexts. These findings offer a proof-of-concept framework contributing to theoretical advances in Technology-enhanced Informal Learning and Design for Sustainable Behavior, and offer methodological insights for educators, architects, and policymakers.

Keywords: Educational Engineering; Generative AI Design; Sustainability Education; Smart Learning Environments; Human-Computer Interaction; Reinforcement Learning

1 Introduction

The rapid pace of global urbanization presents one of the most formidable challenges of the 21st century. By 2050, it is projected that over two-thirds of the world's population will reside in urban centers, placing unprecedented strain on resources, infrastructure, and the environment [31]. The building sector is a major contributor to global energy consumption and carbon emissions, accounting for approximately 40% of total energy use [16]. Consequently, the pursuit of urban sustainability has transitioned from a peripheral concern to a critical imperative.

Conventional approaches to sustainable architecture have primarily focused on material science and energy systems. While these efforts have yielded significant technical gains, a persistent "performance gap"–where actual energy consumption exceeds predicted values by 20-50%–remains, largely attributable to insufficient consideration of occupant behavior [13, 22]. A highly efficient building may fail to achieve its sustainability targets if its occupants do not engage in energy-conserving practices. This gap highlights a critical disconnect not only between physical design and behavioral psychology, but also between technological infrastructure and environmental education.

This paper argues that the built environment itself can serve as a powerful educational medium. Drawing on the concept of the "hidden curriculum" in educational theory–the idea that learning occurs implicitly through the structures and environments in which people are embedded–we propose that intelligently designed spaces can educate occupants about sustainability through daily interaction, without relying solely on formal instruction [17]. To realize this potential, this study proposes a novel cross-disciplinary framework that integrates AI-driven generative design with principles from Educational Engineering, HCI, and learning sciences.

Our central research objective is to develop and evaluate an AI system capable of generating spatial layouts that are not only energy-efficient by design but also function as an educational intervention, providing actionable feedback to guide occupants toward reduced energy use, responsible

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waste management, and mindful consumption. This research makes three key contributions to the field of Educational Engineering. First, it introduces a theoretical model synthesizing generative design algorithms with experiential and situated learning theories within physical spaces. Second, it provides simulation-based evidence demonstrating the dual benefits of AI-optimized design in reducing energy consumption and fostering informal sustainability education. Third, it employs economic diversity metrics to evaluate the adaptability of these AI-generated educational environments across diverse cultural and pedagogical contexts.

2 Literature Review

2.1 Generative Design and AI in Spatial Learning Environments

Generative design, a paradigm shift in design methodology, leverages computational algorithms to autonomously generate a multitude of design alternatives based on predefined parameters and objectives [24]. In architecture and urban planning, it has been employed to optimize structural integrity, material usage, and spatial connectivity [18, 25]. Recent studies have demonstrated the utility of generative adversarial networks (GANs) and reinforcement learning (RL) in creating novel building layouts that respond to environmental and social constraints [10, 23].

However, a significant gap persists in the application of generative design to educational contexts. While research on smart campuses and technology-enhanced learning environments has grown substantially, the systematic use of AI to generate physical spaces optimized for informal learning outcomes remains largely unexplored [28]. The integration of RL to refine generative processes for pedagogical objectives represents a particularly underexplored frontier [29].

2.2 Technology-Enhanced Informal Learning and Environmental Literacy

Educational Engineering increasingly recognizes that meaningful learning occurs beyond formal classroom settings. Informal learning environments, augmented by technology, play a crucial role in developing 21st-century competencies, including environmental literacy and self-regulated behavior [32]. Smart building management systems, when integrated with HCI principles, can provide real-time data and feedback, transforming passive occupants into active learners engaged in ongoing sustainability practices [5, 33].

The concept of “learning analytics” is particularly relevant here. By monitoring and analyzing occupant interactions with intelligent building systems–such as thermostat adjustments, lighting usage, and waste sorting patterns–it becomes possible to generate actionable insights about the effectiveness of spatial design as an educational intervention [8]. This data-driven approach aligns with the Educational Engineering mandate to empirically validate and iteratively improve learning environments.

2.3 Design for Sustainable Behavior as Situated Learning

Design for Sustainable Behavior (DfSB) is an interdisciplinary field that seeks to influence human behavior towards more sustainable practices through design interventions [3]. DfSB strategies often involve nudges, feedback mechanisms, and persuasive technologies embedded within products, services, and environments [21]. When viewed through an educational lens, these interventions can be understood as forms of situated learning–a theory positing that knowledge is inseparable from the context in which it is acquired and applied [19].

By making sustainable choices salient and providing immediate, contextual feedback on resource consumption, intelligent spatial design acts as a “hidden curriculum,” implicitly educating users on environmental responsibility through daily practice [11]. Studies have shown that well-designed interactive systems can significantly impact user behavior by making sustainable options more salient, attractive, and easy to adopt [27]. However, a persistent challenge lies in scaling these behavioral-educational interventions beyond individual products to broader spatial systems, and in integrating them into the initial design phase of physical spaces [2].

2.4 Research Gaps

Despite significant advancements in each of these domains, a critical research gap persists at their intersection. Generative design excels at optimizing physical parameters but rarely incorporates educational psychology as a core objective function. Similarly, DfSB and HCI research have demonstrated success in influencing behavior, but often within existing environments, rather than shaping the fundamental spatial layout from the ground up. The current literature lacks a comprehensive framework that synergistically combines AI-driven generative design with learning science principles to create environments that are inherently conducive to sustainability education. This study aims to bridge this gap.

3 Methodology

Our research methodology is structured to rigorously investigate the efficacy of an AI-driven generative design framework in promoting sustainable learning and behavioral transformation. This involves the development of a novel computational design system, the collection and processing of a substantial dataset, a controlled experimental simulation, and the application of advanced statistical methods.

3.1 System Architecture: EcoDesign-GAN

We developed EcoDesign-GAN, which integrates Conditional Wasserstein GAN with Gradient Penalty (WGAN-GP) [12] with Proximal Policy Optimization (PPO) [26] to produce optimized spatial layouts. The architecture comprises three interlocked modules.

The Generator Network (G) is a conditional WGAN-GP that generates floor plans based on site constraints (area, orientation, room adjacency rules, and climate zone). The generator uses a series of transposed convolutional layers with batch normalization and ReLU activation, mapping a 128-dimensional latent space to 256 by 256 pixel layout representations.

The Discriminator Network (D) is a multi-objective discriminator evaluating both energy performance (via EnergyPlus simulation interface) and Educational Nudge Potential (ENP)–a rule-based score assessing spatial features that facilitate informal learning and actionable feedback (e.g., proximity of smart interfaces to high-traffic areas, visibility of resource consumption data, accessibility of sustainable choice points).

The Reinforcement Learning (RL) Agent is a PPO agent refining latent space parameters based on discriminator feedback. The reward function R combines four weighted objectives:

$$R = w_1(-E) + w_2 D + w_3(-C) + w_4 ENP$$

where E = normalized annual energy consumption (kWh/m^2), D = daylight autonomy (%), C = construction cost proxy, and ENP = Educational Nudge Potential score (0-1). Weights were empirically tuned via sensitivity analysis: $w_1 = 0.4$, $w_2 = 0.2$, $w_3 = 0.2$, $w_4 = 0.2$. This adversarial process, augmented by RL-based exploration, refines the Generator's output over 50,000 training episodes.

3.2 Data Collection and Processing

To train and validate EcoDesign-GAN, a dataset of 5,000 urban unit layouts was compiled from publicly available architectural plans and urban planning archives across five major global cities (New York, London, Tokyo, Shanghai, and Berlin) to ensure geographical and typological diversity. For each unit, spatial layout, building characteristics, energy performance data, and occupant behavioral data were collected and processed.

Occupant behavioral data was available for a subset of 1,247 units (24.9%) equipped with smart home systems. For the remaining 3,753 units, behavioral proxies were imputed using K-nearest neighbors (K = 5) based on unit size, location, and demographic similarity, following established imputation practices for missing behavioral data in building energy research [20]. Data augmentation (rotation, mirroring) was applied to increase effective sample size by 4×.

3.3 Experimental Design: Controlled Simulation

The experimental design involved a controlled simulation comparing 100 case-control pairs of AI-optimized layouts (generated by EcoDesign-GAN) against traditional, human-designed layouts. Pairs were matched on gross floor area (±10%), climate zone, occupancy density, and construction cost tier. Traditional designs were sourced from architectural competition entries certified by local green building standards (LEED, BREEAM).

The simulation was conducted using EnergyPlus 23.1 [6] integrated with a custom agent-based behavioral simulation module. The behavioral module integrated the Theory of Planned Behavior [1] for intentional actions and Fogg's Behavior Model [7] for habit-driven behaviors. Parameters were calibrated using the 1,247-unit validation subset, achieving RMSE = 0.12 for energy-related actions.

3.4 Metrics

Three key metrics were used to evaluate the framework's effectiveness.

The Energy Efficiency Index (EEI) is defined as total annual energy consumption (kWh/m^2) per unit, calculated from EnergyPlus output for heating, cooling, lighting, and appliances.

The Educational Nudge Effectiveness (ENE) is a composite score (0-1) quantifying both the frequency of sustainable behaviors and the simulated acquisition of environmental awareness through spatial feedback. ENE integrates waste sorting compliance rate, energy-saving thermostat setting duration, daylight utilization rate, and water conservation behavior index. Critically, the ENE metric extends beyond simple behavioral frequency to capture the degree to which occupants demonstrate learning through their adaptive responses to spatial feedback over the simulation period.

The Design Diversity Metrics (HHI and Gini Coefficient) assess the diversity and equity of generated learning environments. A lower HHI (< 0.25) indicates greater design diversity, suggesting the GAN's ability to generate varied environments suitable for diverse educational contexts. The Gini coefficient measures the equity of energy distribution across units, ensuring that the benefits of sustainable design are broadly shared.

3.5 Statistical Analysis

Statistical analysis was performed using Python 3.9 with SciPy 1.10 and Pandas 2.0. Paired t-tests compared EEI and ENE between AI-optimized and traditional layouts ($\alpha = 0.05$, two-tailed). Effect sizes were reported as Cohen's d with 95% confidence intervals. Multiple linear regression identified significant correlations between specific design features and outcomes, with Variance Inflation Factor (VIF < 5) checked for multicollinearity. Bootstrapping (n = 1,000 resamples) validated the robustness of HHI and Gini coefficient estimates.

4 Results

4.1 Efficiency Gains in Energy Consumption

Paired t-tests demonstrated a statistically significant reduction in EEI for AI-optimized units (M = 85.2 kWh/m^2/year, SD = 7.8) compared to traditional units (M = 113.6 kWh/m^2/year, SD = 9.2), t(99) = -25.8, $p < 0.001$, Cohen's d = 2.8 (95% CI: 2.4-3.2). This represents a mean relative reduction of 25% (95% CI: 22.3%-27.7%) in annual energy consumption. Key drivers included optimized building orientation for passive solar gain (ΔEEI = -12.3 kWh/m^2), cross-ventilation pathways (ΔEEI = -8.7 kWh/m^2), and high-performance envelope materials (ΔEEI = -7.4 kWh/m^2).

4.2 Educational Nudge Effectiveness and Informal Learning Outcomes

The ENE score for AI-optimized units (M = 0.72, SD = 0.08) was significantly higher than for traditional units (M = 0.51, SD = 0.07), t(99) = 21.5, $p < 0.001$, Cohen's d = 2.4. This indicates a 40% relative increase in ENE, translating to measurable improvements in simulated learning-through-practice outcomes.

Waste Sorting as a Situated Learning Activity: Clearly demarcated multi-compartment waste stations integrated into kitchen designs, paired with visual feedback labels, led to a 60% increase in proper waste segregation (AI: 78% compliance vs. Traditional: 49% compliance). This design pattern functions as a daily, contextual learning prompt, reinforcing environmental literacy through repeated, low-effort practice.

Energy Awareness through Interactive Feedback: Smart thermostat interfaces strategically placed in high-traffic areas, providing real-time visual feedback on energy consumption, encouraged occupants to maintain energy-saving settings for 70% longer durations (AI: 6.8 hours/day vs. Traditional: 4.0 hours/day). This finding is consistent with educational research demonstrating that immediate, actionable feedback is a critical driver of learning and behavior change [14].

Lighting Literacy: Proximity of light switches to natural light sources and intuitive zoning resulted in a 35% reduction in unnecessary artificial lighting use during daylight hours, suggesting that spatial design can educate occupants about natural resource availability without explicit instruction.

These results underscore the power of spatial design as an informal educational medium. However, it is important to emphasize that these results reflect simulated behaviors calibrated against limited real-world data (n = 1,247 validation subset) and require empirical validation in physical environments.

4.3 Diversity and Adaptability of AI-Generated Learning Environments

The HHI for AI-optimized layouts was consistently low (average HHI = 0.15, SD = 0.03), significantly lower than human-designed layouts (average HHI = 0.38, SD = 0.05), t(198) = -18.2, $p < 0.001$. This high diversity indicates that EcoDesign-GAN can generate a broad range of spatial configurations suitable for diverse cultural contexts and pedagogical needs, avoiding the homogenization that could limit the effectiveness of informal learning environments.

The Gini coefficient for energy distribution across AI-generated units was G = 0.12 (vs. G = 0.23 for traditional designs), indicating a more equitable distribution of sustainability benefits. This equity dimension is particularly relevant from an educational standpoint, as it suggests that the learning opportunities embedded in AI-optimized spaces are broadly accessible rather than concentrated in a few premium units.

4.4 Design Complexity and Learning Effectiveness

Regression analysis revealed a moderate positive correlation (r = 0.45, $p < 0.01$) between spatial complexity (number of distinct functional zones, connectivity index) and ENE score. This finding aligns with educational theories suggesting that richer, more varied environments provide more opportunities for experiential learning. However, quadratic regression revealed diminishing returns beyond an optimal complexity threshold (inflection point at connectivity index ≈ 4.2), indicating that excessive spatial intricacy may hinder rather than support intuitive sustainable actions–a finding with direct implications for the design of effective learning environments.

5 Discussion

This study presents a compelling proof-of-concept for the transformative potential of AI-driven generative design in fostering sustainability education through the built environment. Our findings extend beyond conventional approaches to sustainable architecture by demonstrating that computational design can not only optimize physical parameters for energy efficiency but also function as an informal educational intervention, cultivating environmental literacy through daily spatial interactions.

5.1 The Built Environment as a Hidden Curriculum

The EcoDesign-GAN framework exemplifies how physical spaces can act as a "hidden curriculum" for sustainability. The strategic placement of interactive feedback systems, accessible sustainable choice points, and intuitive spatial cues transforms the act of daily living into a continuous, situated learning experience [19]. This perspective reframes the role of architectural design within Educational Engineering: rather than viewing smart buildings merely as energy-optimization tools, we propose understanding them as dynamic learning environments that implicitly educate occupants about resource consumption and environmental responsibility.

This shift has significant implications for the design of educational facilities. University campuses, student dormitories, and community centers represent high-impact contexts where AI-optimized spatial design could reinforce formal sustainability curricula through lived experience. A student who daily interacts with a smart thermostat providing real-time energy feedback is not merely conserving energy; they are acquiring environmental literacy through practice–a form of learning that research suggests is more durable and transferable than abstract instruction alone [32].

5.2 Implications for Educational Engineering Practice

The findings of this study offer several actionable insights for the field of Educational Engineering. First, the ENE metric developed in this study provides a novel instrument for evaluating the educational effectiveness of spatial designs, complementing traditional measures of energy performance with an assessment of learning-through-practice outcomes. Second, the EcoDesign-GAN framework demonstrates how learning analytics principles can be extended from digital platforms to physical environments, using behavioral data from smart building systems to iteratively improve the educational effectiveness of spatial configurations. Third, the high

Metric	AI-Optimized (M ± SD)	Traditional (M ± SD)	t-statistic	p-value	Cohen's d
EEI (kWh/m^2/year)	85.2 ± 7.8	113.6 ± 9.2	-25.8	< 0.001	2.8
ENE Score (0-1)	0.72 ± 0.08	0.51 ± 0.07	21.5	< 0.001	2.4
HHI (Design Diversity)	0.15 ± 0.03	0.38 ± 0.05	-18.2	< 0.001	–
Gini (Energy Equity)	0.12	0.23	–	–	–

Table 1. Summary of Key Performance Metrics: AI-Optimized vs. Traditional Layouts

design diversity (HHI = 0.15) of AI-generated layouts suggests that this approach can be adapted to diverse cultural and institutional contexts, a critical consideration for the global scalability of sustainable education initiatives.

5.3 Ethical Considerations of Educational Nudging

The observed effectiveness of spatial nudges in promoting sustainable behaviors raises important ethical considerations, particularly within an educational context. While nudges are generally considered less coercive than mandates, their subtle influence on decision-making warrants careful scrutiny [30]. In educational settings, there is a particular responsibility to ensure that behavioral interventions foster genuine cognitive development and critical thinking, rather than mere behavioral conditioning. Future deployments should incorporate "nudge disclosure"–informing occupants about embedded design intentions–and provide opt-out mechanisms for smart systems, ensuring that sustainable living is a choice facilitated by design, not imposed by it.

5.4 Scalability and Future Research Directions

The methodology employed in this study suggests significant potential for scalability. By training EcoDesign-GAN on diverse data from multiple cities, we have demonstrated preliminary applicability across varied geographical, cultural, and climatic contexts. However, several critical limitations must be acknowledged.

The primary limitation is the simulation-to-reality gap. The occupant behavioral and learning data were based on proxies and agent-based simulations rather than comprehensive real-world observations. The 40% improvement in ENE reflects simulated environments and requires empirical validation through real-world pilot projects, longitudinal studies tracking behavior change over months and years, and cross-cultural validation of nudge effectiveness. Future research priorities include empirical validation in educational facilities (e.g., university dormitories, smart campuses), long-term impact studies on the durability of behavior change and potential "nudge fatigue," and analysis of whether AI-optimized designs are equitably accessible across socioeconomic strata.

6 Conclusion

This study has successfully demonstrated the proof-of-concept efficacy of EcoDesign-GAN in simultaneously optimizing spatial layouts for energy efficiency and promoting sustainable occupant behaviors as a form of informal learning. By integrating principles from AI, HCI, and Educational Engineering, we have presented a novel cross-disciplinary approach that addresses the complex interplay between the built environment, human behavior, and environmental education.

Our large-scale simulations revealed a 25% reduction in energy consumption (Cohen's d = 2.8, $p < 0.001$), a 40% improvement in Educational Nudge Effectiveness (simulated), high design diversity (HHI = 0.15) ensuring contextual adaptability, and equitable distribution of sustainability benefits (Gini = 0.12). These findings underscore the potential of AI to act as a co-creator in shaping more sustainable and educationally enriching built environments.

As a simulation-based study with limited real-world behavioral validation, these findings represent promising theoretical and methodological advances rather than definitive evidence of real-world effectiveness. We explicitly call for empirical validation through physical pilot projects in educational facilities, longitudinal studies of learning and behavior change durability, and critical examination of the ethical implications of AI-driven behavioral influence. This study lays a foundation for a new era of Educational Engineering in which the design of physical spaces is recognized as a powerful, scalable instrument for sustainability education.

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