Harnessing Evolutionary Machine Learning for Net-Zero Construction: A Strategic Path to Sustainable Performance

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Abstract. This study explores how Evolutionary Machine Learning (EML), an adaptive optimization approach within artificial intelligence, can drive the transition toward net-zero construction and sustainable business performance. Drawing on Ecological Modernization Theory, Adaptive Structuration Theory, and the Diffusion of Innovation framework, the research develops and empirically tests a strategic model explaining how EML-enabled technologies enhance both carbon neutrality and organizational outcomes. Using survey data from 213 Vietnamese construction firms, the findings reveal that the success of EML adoption depends on aligning technological integration with operational realities, stakeholder readiness, and long-term innovation strategies. EML is shown to optimize resource allocation, project scheduling, and carbon footprint management, providing firms with competitive and environmental advantages. The study contributes to sustainable digital transformation discourse by positioning EML as a practical tool for solving complex optimization challenges in developing economies, offering actionable insights for policymakers, practitioners, and researchers seeking to leverage intelligent systems for climate-resilient and high-performing construction supply chains.

Keywords: Evolutionary Machine Learning (EML); Net-Zero Construction; Sustainable Performance; Technology Adoption; Business Optimization First Section

1 Introduction:

By 2030, the construction industry is expected to account for approximately 14.7% of global GDP, highlighting its growing economic significance alongside increasing concerns over energy consumption, carbon emissions, and occupational safety (Iqbal et al., 2022; Craveiro et al., 2019; Zhang et al., 2025). The need to balance productivity-driven profitability with carbon neutrality has become a persistent challenge for construction firms. Recent studies suggest that the convergence of digital technologies

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and sustainability initiatives may offer viable solutions to this dilemma (Regona et al., 2024; Maqbool, Namaghi, et al., 2023; Maqbool, Saiba, et al., 2023).

Within the Construction 4.0 paradigm, digital technologies such as Building Information Modeling, Internet of Things, digital twins, and blockchain have reshaped construction processes (Ohueri et al., 2023; Oyejobi et al., 2024). In this context, Evolutionary Machine Learning (EML), derived from evolutionary computation and genetic algorithms, has emerged as a promising approach for solving multi-objective optimization problems under uncertainty (Carvalho et al., 2024). Unlike traditional machine learning, EML does not rely on gradient-based optimization or fully labeled datasets, making it well suited to the dynamic and fragmented nature of construction projects (Boulesnane, 2024; Yuan et al., 2024). Recent evidence indicates that integrating EML into BIM environments enables the simultaneous optimization of cost, structural efficiency, and environmental performance—capabilities that exceed those of single-objective models (Yavan et al., 2024). Nevertheless, empirical research examining the impact of EML on sustainability outcomes, particularly carbon neutrality, remains scarce.

Despite the recognized benefits of artificial intelligence, its adoption in the construction sector continues to be limited by high implementation costs, skill shortages, and organizational disruption (Newman et al., 2021). These barriers are amplified in developing countries, where firms face financial constraints, resistance to change, and rigid organizational structures (Pham et al., 2020; Huynh-Xuan et al., 2024; Regona et al., 2024). As a result, many organizations remain in the early stages of AI-driven transformation, and the mechanisms through which advanced analytics contribute to both environmental and business performance are not yet fully understood (Luqman et al., 2024).

To address this gap, this study integrates Ecological Modernization Theory (EMT), Adaptive Structuration Theory (AST), and Diffusion of Innovation (DOI) theory to develop a unified conceptual model explaining how EML-enabled technologies facilitate carbon emission reduction and performance improvement in construction firms. This theoretical integration offers a multi-level analytical lens that captures both technological attributes and human–organizational dynamics, overcoming the limitations of single-theory approaches.

Accordingly, this study addresses the following research questions:

RQ1: How can EML-enabled technologies be effectively adopted in construction projects?

RQ2: Do these technologies enhance carbon neutrality and business performance?

2 Hypothesis Development

According to Diffusion of Innovation (DOI) theory, five attributes—relative advantage, observability, compatibility, complexity, and trialability—shape how innovations are adopted and institutionalized within organizations (Rogers, 2003). In the construction industry, which is characterized by low digital maturity, these attributes are critical in determining whether Evolutionary Machine Learning (EML) can be effectively implemented to support sustainability and performance objectives.

2.1 DOI Attributes and Carbon Neutrality

Relative advantage reflects the perceived superiority of EML over traditional practices. By enabling data-driven optimization of resources, schedules, and energy use, EML enhances efficiency while reducing carbon emissions and costs (Regona et al., 2024; Hussain et al., 2024; Nikoukar & Tavakolan, 2025). Observability refers to the extent to which EML outcomes are visible; its iterative analytics allow firms to monitor measurable improvements in emissions, waste, and energy efficiency, thereby strengthening commitment to carbon neutrality (Carvalho et al., 2024; Yavan et al., 2024).

H1a. Relative advantage positively influences carbon neutrality initiatives.
H1b. Observability positively influences carbon neutrality initiatives.

Compatibility indicates alignment between EML and existing organizational processes and sustainability goals. Poor alignment may create resistance and limit environmental gains, particularly in digitally immature construction firms (Newman et al., 2021; Saleem et al., 2024). Complexity captures perceived difficulty of use; although high complexity may hinder adoption, appropriate training and managerial support can mitigate this barrier and enhance environmental performance (Turner et al., 2021; Shaik et al., 2024). Trialability enables firms to experiment with EML on a limited scale, reducing uncertainty and facilitating learning related to emission reduction (Zhang & Li, 2022).

H1c. Compatibility positively influences carbon neutrality initiatives.
H1d. Complexity positively influences carbon neutrality initiatives.
H1e. Trialability positively influences carbon neutrality initiatives.

2.2 DOI Attributes, Carbon Neutrality, and Business Performance

EML adoption not only supports environmental objectives but also enhances business performance. Through optimized resource allocation and risk assessment, EML improves productivity, cost efficiency, and site safety (Hussain et al., 2024; Peng et al., 2023). When EML aligns with organizational systems (compatibility), is managed through capability development (complexity), and is introduced incrementally (trialability), firms benefit from higher returns on investment and operational agility (Özbek et al., 2022; DeSanctis & Poole, 1994).

H2a. Relative advantage positively influences business performance.
H2b. Observability positively influences business performance.
H2c. Compatibility positively influences business performance.
H2d. Complexity positively influences business performance.
H2e. Trialability positively influences business performance.

Carbon neutrality further acts as a strategic mechanism for value creation, as regulatory compliance, stakeholder trust, and market differentiation contribute to long-term competitiveness (Mukherjee et al., 2023; Özbek et al., 2022).

H3. Carbon neutrality initiatives positively influence business performance.

Figure 1, presents the proposed research model.

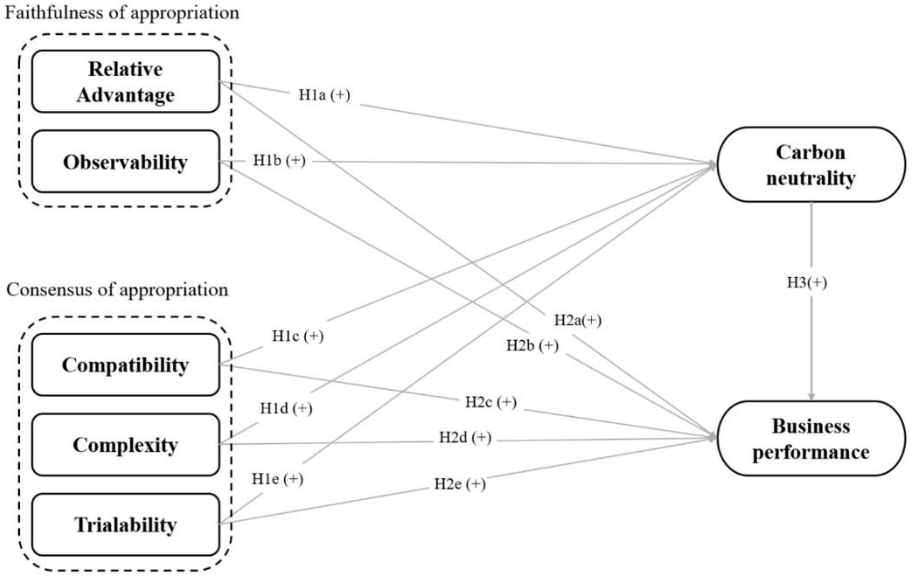

Fig. 1. Hypothesis model of this study

3 Methodology:

3.1 Target Sample

Vietnam represents a suitable context for examining EML adoption in construction due to its rapid economic growth and increasing policy emphasis on digital transformation and sustainability. GDP growth is projected to reach 7.1% by 2024, with industry and construction contributing significantly to national development (IMF, 2025; Vietnam, 2025a). Although the construction sector recorded a growth rate of 7.32% in early 2025 (National Statistics Office of Vietnam, 2025b), digital transformation remains constrained by limited financial resources, high technology costs, and shortages of skilled labor (Pham et al., 2020).

To address these challenges, the Vietnamese government has introduced policies promoting digitalization and sustainability, including energy monitoring (Decision No. 280/QD-TTg), sustainable building materials (Decision No. 1266/QD-TTg), and mandatory BIM adoption in public projects (Decision No. 258/QD-TTg) (The Prime Minister, 2019, 2020; Ngoc et al., 2024). Against this backdrop, this study targets

Vietnamese construction firms that have adopted EML-enabled technologies. Based on records from the General Statistics Office of Vietnam, 862 eligible firms were identified and invited to participate.

3.2 Data Collection

Data were collected through an online questionnaire survey designed to examine the effects of EML-enabled technologies on carbon neutrality and business performance. The target respondents were senior managers from construction firms involved in infrastructure development and sustainability initiatives. To ensure clarity and content validity, the questionnaire was translated into Vietnamese and back-translated into English. A pilot study involving 100 firms was conducted to refine the measurement items.

The final survey was distributed via email to 862 executives between June and October 2024, with two follow-up reminders. A total of 279 responses were received, yielding a response rate of 32.4%. After data screening, 213 valid responses remained for analysis. This sample size exceeds the minimum requirement for Structural Equation Modeling, ensuring adequate statistical power (Boomsma & Hoogland, 2001; Kline, 2023).

4 Results Analysis

4.1 Descriptive Analysis

In Table 1, we summarize data from 213 companies: 46% are private, 28.2% are state-owned, and 25.8% are joint ventures. Approximately 47.4% are engaged in design, 22.1% in construction, and 14.1% in planning. While 70% of those considered SMEs have fewer than 200 employees, half of these self-identify as having fewer than 50 employees. Of the respondents, 56.3% are classified as managers, while 43.7% are executives, providing both strategic and operational perspectives. Most respondents working in design (34%), project management (28.2%) or business management (20.6%) provided only different perspectives on EML integration activities across the Vietnamese construction industry.

Table 1. Descriptive analysis of participating firms and respondents

Characteristics	N = 213 (%)
Company Ownership Structure	
100% locally owned	60 (28.2%)
100% privately-owned	98 (46%)
Joint venture	55 (25.8%)
Company Operation Field	

Design	101 (47.4%)
Construction	47 (22.1%)
Project Management	18 (8.5%)
Zoning	30 (14.1%)
Invest	9 (4.2%)
Other	8 (3.8%)
Business Size (full-time employees)	
Less than 50	106 (49.8%)
From 50-200	43 (20.2%)
From 200-500	19 (8.9%)
Over 500	45 (21.1%)
Job Title of Participants	
Top-level manager	61 (28.6%)
Middle-level manager	55 (25.8%)
First-level manager	4 (1.9%)
Coordinator	93 (43.7%)
Working Department of Participants	
Board of Manager	43 (20.6%)
Design department	71 (34%)
Project Management department	60 (28.7%)
Procurement department	8 (3.8%)
Construction department	12 (5.7%)
Business department	7 (3.3%)
Human Resources department	2 (1.0%)
Finance department	1 (0.5%)
Other	5 (2.4%)

4.2 Structural Model Analysis

As shown in Figure 2, the analysis examined how EML-enabled technologies influence carbon neutrality and business performance in construction firms. Results revealed that Observability ($\beta = 0.842$, $p < 0.01$), Compatibility ($\beta = 0.156$, $p < 0.1$), and Complexity ($\beta = 0.307$, $p < 0.01$) positively affected carbon neutrality, with Observability exerting the strongest influence. In contrast, Relative Advantage ($\beta = -0.025$, $p > 0.1$) had no effect, and Trialability ($\beta = -0.460$, $p < 0.01$) negatively impacted carbon neutrality, supporting H1b, H1c, and H1d but not H1a or H1e.

For business performance, positive effects were found for Observability (β = 0.378, $p < 0.01$), Complexity (β = 0.144, $p < 0.05$), and Trialability (β = 0.689, $p < 0.01$), while Relative Advantage (β = -0.436, $p < 0.01$) and Compatibility (β = -0.503, $p < 0.01$) showed negative influences. Thus, H2b, H2d, and H2e were supported. Additionally, carbon neutrality significantly improved business performance (β = 0.364, $p < 0.01$), confirming H3. Finally, the model had moderate to strong explanatory power with R^2 = 0.68 for carbon neutrality and R^2 = 0.72 for business performance.

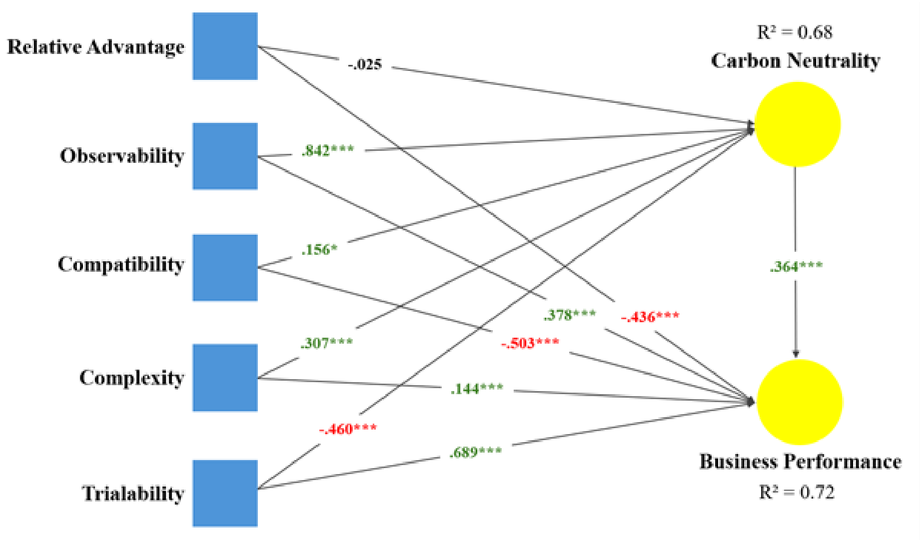

Fig. 2. Structural model analysis of this study

5 Discussion:

The results indicate that EML adoption attributes—particularly observability and complexity—positively influence both carbon neutrality initiatives and business performance, consistent with prior studies (Mamun, 2018; Regona et al., 2024; Wang & Guo, 2022). Observability emerges as the strongest driver, suggesting that visible and measurable EML outcomes motivate continued investment by improving operational efficiency and reducing emissions through real-time monitoring and energy forecasting. Effective managerial support, targeted training, and structured digital environmental policies further mitigate integration complexity and enable low-carbon, efficient operations (Ebekozien et al., 2024; Zhong et al., 2025).

In contrast, relative advantage does not support carbon reduction and negatively affects business performance, while compatibility facilitates environmental goals but fails to generate financial gains. These findings diverge from Regona et al. (2024) and reflect data constraints, skill shortages, and low digital readiness in Vietnam's fragmented construction sector, which limit EML's optimization potential and increase integration costs (Momade et al., 2024; Turner et al., 2021).

Trialability exhibits a mixed effect: short-term EML experiments increase energy use and emissions, but gradual implementation improves learning, risk management, and long-term performance (Zhao et al., 2010). Finally, carbon neutrality significantly enhances business performance by strengthening regulatory compliance, stakeholder trust, and corporate reputation, positioning sustainability as a strategic driver of long-term competitiveness (Meng et al., 2024; Mukherjee et al., 2023).

6 Implications:

This study advances the literature by demonstrating how EML-enabled technologies reconcile carbon neutrality and business performance in the construction industry. By integrating Ecological Modernization Theory, Adaptive Structuration Theory, and Diffusion of Innovation theory, the findings show that EML facilitates energy optimization, emission reduction, and operational efficiency, thereby strengthening environmental performance, stakeholder trust, and long-term competitiveness. Importantly, this study extends existing research by providing empirical evidence from a developing economy, highlighting how post-adoption EML use supports the transition toward net-zero construction despite persistent challenges related to system incompatibility and skill shortages.

From a practical perspective, the results suggest that EML adoption should be treated as a long-term strategic commitment rather than a short-term technological upgrade. Construction firms should invest in employee training, stakeholder engagement, and organizational restructuring to fully realize EML's environmental and economic benefits. Given the delayed realization of returns, staged implementation and rigorous cost–benefit analysis are essential, particularly in digitally immature contexts. Integrating EML with complementary technologies such as BIM and blockchain can further enhance real-time monitoring, regulatory compliance, and organizational resilience, enabling firms to embed sustainability into core operations and achieve durable competitive advantages.

7 Limitations and Future Research

This study has several limitations. First, its cross-sectional design restricts insights into how EML-enabled capabilities and sustainability outcomes evolve over time. Longitudinal studies are needed to capture dynamic learning effects and organizational adaptation. Second, the analysis focuses at the firm level, whereas sustainability transitions are also shaped by supply chains, regulatory frameworks, and broader institutional contexts. Future research should therefore adopt multi-level perspectives to examine how EML contributes to supply chain decarbonization, circular economy initiatives, and policy-driven carbon neutrality strategies.

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