Contextually Adaptive AI-BIM for Sustainable Construction

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Abstract

Artificial Intelligence (AI) is transforming the Architecture, Engineering, and Construction (AEC) industry, particularly through integration with Building Information Modeling (BIM) to enable data-driven sustainability. However, AI-BIM implementation in emerging economies like Indonesia remains fragmented and constrained. As Asia's second-largest construction market, Indonesia faces the dual challenge of accelerating digital transformation while overcoming socio-technical barriers that limit equitable access to AI-driven technologies. Current AI-BIM frameworks are typically computationally intensive, hardware-dependent, and poorly aligned with local design practices, restricting their scalability in medium-scale public projects where resource efficiency and affordability are essential. This research addresses this gap by developing AI-BIM systems that are contextually responsive, lightweight, and capable of operating within infrastructural constraints while delivering measurable sustainability outcomes.

This study proposes a novel Small Language Model - Building Information Modeling framework that redefines how intelligent systems can support sustainable construction in Indonesia's public sector, that affects the AEC education. Unlike conventional Large Language Model based workflows that require extensive computational resources, SLMs are compact, adaptive, and capable of generating real-time sustainability assessments within modest computing environments. The primary objective of this research is threefold: (1) to quantify performance improvements in terms of energy efficiency (kWh/m^2), material waste reduction (kg/m^2), and carbon emission reduction (kgCO_2e/m^2) compared with baseline BIM workflows; (2) to develop a scalable and replicable AI-supported decision-making model for sustainable design and construction; and (3) to evaluate the regulatory, institutional, and workforce readiness necessary to integrate SLM-BIM at the national level.

The study employs a mixed-method research design, integrating a systematic literature review, case study analysis of selected medium-scale public buildings in Indonesia's new capital region (IKN Nusantara), and empirical simulations of material, energy, and emission performance using BIM-based digital twins. This triangulated approach enables the validation of quantitative and qualitative sustainability performance indicators while ensuring methodological robustness across spatial, temporal, and operational dimensions of construction performance assessment. The empirical findings show that the SLM-BIM framework can reduce computational costs, increase material efficiency, and lower operational carbon emissions relative to conventional BIM methods. Beyond technical outcomes, the research also highlights institutional implications: the integration of SLM-BIM enhances data transparency, supports real-time environmental decision-making, and promotes workforce upskilling through AI-assisted design tools that are accessible to even mid-tier construction firms thereby bridging the current technological divide between advanced and emerging economies in digital construction practices.

The preliminary findings lay the groundwork for policy recommendations, such as establishing an AI-sustainability protocol for public buildings, offering incentives for digital capacity building, and providing regulatory support for integrating SLM-BIM into Indonesia's green construction agenda. The findings also highlight the importance of digital literacy, human-AI interaction, and critical thinking as essential competencies for construction education and workforce readiness. The framework contributes to the body of

knowledge by adapting and integrating existing models into a transferable, task-level method and to educational practice by offering evidence-based guidance for curriculum design, industry training, and policy development. The study also addresses the limitations of the proposed method and identifies areas for future research. The research supports Indonesia's long-term climate mitigation strategy by situating this work within the global discourse on sustainable and equitable AI deployment. Also, it advances the development of scalable, resource-efficient AI frameworks for sustainable construction in other emerging economies.

The framework additionally contributes to construction engineering education by providing a scalable, ethically grounded AI-BIM pedagogical model deployable in resource-constrained academic environments.

Keywords: Small Language Model, Building Information Modeling, Sustainable Construction, Artificial Intelligence.

1. Introduction

Artificial Intelligence (AI) continues to transform the Architecture, Engineering, and Construction (AEC) industry, particularly through its integration with Building Information Modeling (BIM) to enhance precision, efficiency, and sustainability. However, the implementation of AI-enabled BIM (AI-BIM) remains uneven globally. Emerging economies, including Indonesia, the second-largest construction market in Asia, face persistent obstacles in adopting high-computational AI systems. These barriers include limited computing infrastructure, uneven digital literacy, and resource constraints that disproportionately affect medium-scale public construction projects, which constitute a significant portion of Indonesian government building initiatives.

Recent advances in AI highlight the growing relevance of Small Language Models (SLMs), which offer lightweight, efficient alternatives to computationally intensive Large Language Models (LLMs). SLMs provide rapid inference, lower energy requirements, and improved adaptability within constrained environments, making them particularly suitable for AEC workflows in resource-limited contexts. Within this paradigm, the development of an SLM-BIM framework presents new opportunities for sustainable construction practices that are both technologically feasible and operationally scalable. Unlike Large Language Models trained on broad internet-scale corpora, the SLM in this framework is domain-curated using structured BIM datasets and sustainability-specific knowledge, reducing data contamination risks, improving traceability, and aligning with responsible AI principles in engineering practice.

This paper examines the theoretical rationale, methodological structure, and anticipated outcomes of an SLM-BIM sustainability optimization model designed for medium-scale public buildings in Indonesia. The framework integrates machine-learning prediction, constrained optimization, and expert-informed validation to produce measurable improvements in material efficiency, operational energy performance, and carbon emissions. The study situates this contribution within the broader discourse on sustainability assessment, digital transformation, and equitable AI deployment in emerging economies.

2. Background and Literature Review

2.1 Foundations of Sustainability and Green Building

Sustainability is grounded in the Brundtland Commission's definition of intergenerational responsibility, which emphasizes the capacity of present development to meet contemporary needs without compromising future generations. Elkington's Triple Bottom Line framework further operationalizes sustainability into three dimensions: environmental protection, social equity, and economic viability. Green building indicators such as embodied energy, operational energy use, carbon intensity, and material efficiency have been widely recognized as central metrics for sustainable design and assessment [1], [2]. These measurable indicators are reinforced in certification systems such as LEED, BREEAM, and Indonesia's Greenship rating framework.

2.2 BIM Implementation Challenges in Emerging Economies

BIM adoption has accelerated globally due to its capacity to integrate multidisciplinary data, improve communication, and support life-cycle decision-making [3]. However, empirical studies highlight persistent structural barriers to BIM adoption in low- and middle-income countries (LMICs), including limited digital infrastructure, inconsistent training opportunities, lack of interoperable standards, and organizational resistance to technological change [4], [5].

In Indonesia, these structural constraints are amplified by variations in institutional capacity and the dominance of medium-scale public projects that often rely on constrained budgets and limited computational resources. This context underscores the demand for AI-BIM systems that are computationally efficient, adaptable to local workflows, and accessible to small and mid-sized firms operating without high-performance hardware.

2.3 Small Language Models as a Lightweight AI Alternative

Recent research on efficient artificial intelligence deployment has highlighted the growing relevance of Small Language Models (SLMs) as alternatives to computationally intensive Large Language Models (LLMs). SLMs enable faster inference, reduced memory requirements, and improved adaptability in resource-constrained environments [6], [7]. Although SLMs possess narrower generalization capabilities than LLMs, their computational efficiency and domain-specific adaptability make them well suited for BIM-integrated decision-support systems.

These characteristics establish the theoretical foundation for an SLM-driven BIM framework capable of supporting sustainability analysis under resource constraints typical of construction sectors in emerging economies.

2.4 Lightweight Predictive and Optimization Models in Construction

Machine-learning models such as Random Forest regressors are widely used in construction analytics due to their interpretability and robustness when modeling nonlinear relationships in project datasets [8]. Similarly, constrained optimization techniques such as Sequential Least Squares Programming (SLSQP) have been applied to generate feasible design recommendations while respecting real-world project constraints such as cost, constructability, and resource availability.

3. Research Questions and Hypotheses

The study is guided by four central research questions that are (1) To what extent does the proposed SLM-BIM framework improve sustainability performance that is measured by energy efficiency (kWh/m^2), material waste reduction (kg/m^2), and carbon emissions (kgCO_2e/m^2) compared with conventional BIM workflows in medium-scale public building projects in Indonesia? (2) Regarding Model Design, Scalability, and Replicability
How can a Small Language Model BIM decision-support framework be designed to remain computationally efficient, scalable, and replicable across diverse public building contexts in Indonesia? Corresponding hypotheses include measurable performance enhancements (H1), improved computational efficiency (H2), feasibility of incremental optimization (H3), and the predominance of socio-technical rather than algorithmic barriers (H4).

4. Methodology

The methodology follows a mixed-methods structure integrating literature synthesis, empirical modeling, optimization, and qualitative validation. The framework consists of five phases:

4.1 Systematic Literature Review

A systematic review was conducted using Scopus, IEEE Xplore, Web of Science, and ScienceDirect. Search terms included “AI-BIM sustainability,” “SLM construction,” and “green building optimization.” The review identified technical gaps in AI-BIM adoption, performance metrics for sustainable construction, and opportunities for embedding lightweight AI in BIM environments.

Prior studies on AI-BIM integration and digital construction education were also reviewed to identify technological gaps and opportunities for lightweight AI deployment in BIM environments [9], [10].

4.2 Case Study Selection and BIM Data Acquisition

For the purposes of this study, medium-scale public buildings are defined as projects ranging between 5,000-20,000 m^2 gross floor area, with construction values between USD 5-25 million, consistent with Indonesian Ministry of Public Works classifications (2023). Buildings located in Indonesia’s new capital region (Nusantara) were selected as representative case studies. Selection criteria included availability of BIM models (in Revit authoring software), presence of verifiable material and operational datasets, and relevance to recognized sustainability certification frameworks. The case study dataset includes materials schedules, energy usage estimates, resource allocation ratios, and project documentation.

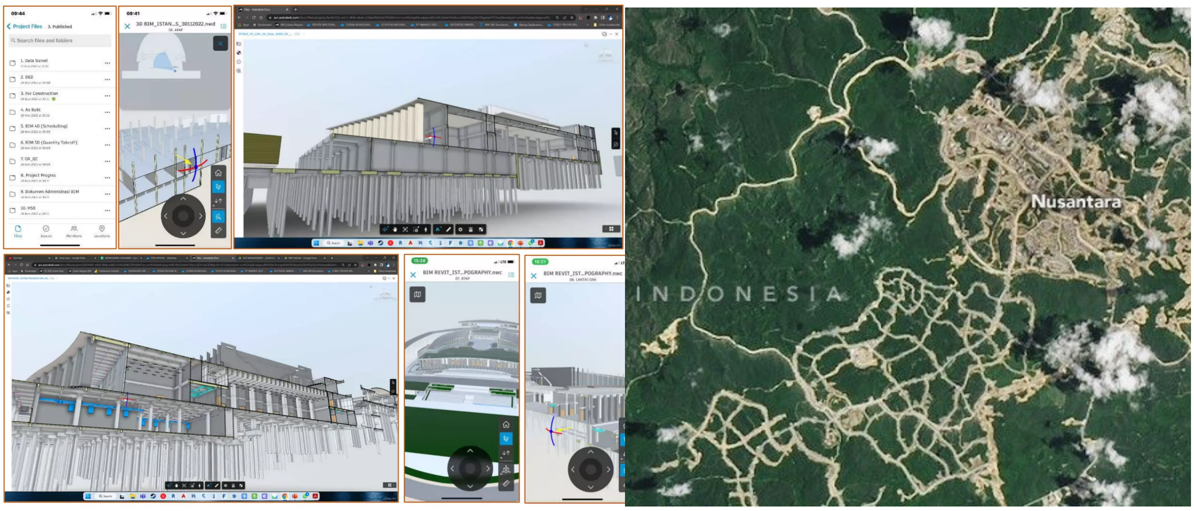

Figure 1. BIM Model of Selected Buildings and the Location Contextual Map

The selected BIM model used for simulation is shown in Figure 1, illustrating the architectural and structural components from which material schedules and energy parameters were extracted.

4.3 Predictive Modeling Using Lightweight Machine Learning

A Random Forest regression model is used to estimate sustainability performance indicators such as energy intensity, material efficiency, and carbon emissions. The model incorporates input variables including normalized resource ratios, construction cost descriptors, project duration, and risk-related attributes. The choice of Random Forest aligns with the need for computational efficiency and model interpretability in environments without dedicated GPU infrastructure. The integration of Small Language Models allows the system to interpret BIM-linked textual data, generate material recommendations, and support normative sustainability reasoning using structured and semi-structured project information.

Table 1. Summary of Input Features and Target Variables for the Predictive Model

Category	Variable	Description	Type	Role in Model
Project Characteristics	Gross Floor Area (m^2)	Total constructed building area	Continuous	Predictor
	Project Duration (months)	Construction schedule length	Continuous	Predictor
	Construction Cost (USD)	Total estimated project cost	Continuous	Predictor
Resource Allocation Metrics	Material Ratio (%)	Proportion of material quantity relative to baseline	Continuous	Predictor
	Labor Ratio (%)	Relative labor allocation	Continuous	Predictor
	Equipment Ratio (%)	Equipment usage intensity	Continuous	Predictor
Environmental Indicators	Energy Intensity (kWh/m^2)	Predicted operational energy demand	Continuous	Target
	Material Waste (kg/m^2)	Construction waste generation	Continuous	Target
	Carbon Emission ($kgCO_2e/m^2$)	Embodied + operational carbon	Continuous	Target
Optimization Output	Sustainability Cost Trade-off Index (SCTI)	Performance-to-cost efficiency metric	Continuous	Evaluation Metric

Table 1 summarizes the structured input features extracted from BIM schedules and project documentation and used in the Random Forest regression model. Rather than relying on high-dimensional unstructured datasets, the model operates on normalized resource allocation ratios and project-level sustainability indicators, enabling computational efficiency while maintaining predictive robustness. Feature normalization was performed to ensure comparability across medium-scale projects ranging from 5,000–20,000 m². The dataset presented serves as the structured input foundation for both predictive modeling and optimization. Resource allocation ratios and energy parameters extracted from BIM schedules were normalized and used as feature variables in the Random Forest regression model.

4.4 Constrained Optimization Layer

Sequential Least Squares Programming (SLSQP) is applied to translate model predictions into actionable sustainability recommendations. The optimization maintains constraints relevant to real-world project delivery that are (1) conservation of total resource allocation; (2) avoidance of extreme deviations from baseline project configurations; (3) cost sensitivity; (4) constructability conditions. This hybrid prediction–optimization approach produces feasible guidance that aligns technical performance with economic and operational considerations.

4.5 Quantitative Evaluation and Expert Validation

Model performance is assessed using MAE, MSE, and R^2 metrics. In addition, a Sustainability Cost Trade-off Index (SCTI) is used to evaluate the relative efficiency of each sustainability improvement. Comparative benchmarking is conducted between conventional BIM workflows, AI-BIM using heavier models, and the proposed SLM-BIM system. The overall research workflow is summarized in Figure 2.

Figure 2. Diagram of Methodology

5. Findings

The findings indicate that the SLM-BIM framework achieves a marked improvement in computational efficiency when compared to LLM-based AI-BIM systems. The interpretability of lightweight models is consistent with findings from previous research demonstrating that reduced model complexity can improve explainability and traceability in engineering decision-support systems [6]. Across the evaluated workflows, SLM-BIM demonstrates significantly lower memory consumption, reduced processing time, and a substantially lighter overall computational load. These efficiency gains stem from the constrained parameter space and domain-specific training strategy of Small Language Models, which limit unnecessary linguistic generalization and focus computation on task-relevant BIM reasoning. As a result, inference operations such as sustainability assessment, design option filtering, and rule-based recommendation generation can be executed without the extensive overhead typically associated with large-scale language models.

Importantly, this computational efficiency translates directly into practical usability within the Indonesian construction context. The reduced hardware requirements enable real-time or near–real-time inference on standard office workstations commonly available in local architectural and engineering firms, without reliance on high-performance GPUs or cloud-based infrastructure. This characteristic is particularly significant for medium-scale public projects, where budgetary constraints and limited access to advanced computing resources often restrict the adoption of AI-driven tools. By enabling responsive decision support under realistic operational conditions, the SLM-BIM approach demonstrates that advanced AI-assisted sustainability analysis can be achieved without sacrificing accessibility, cost efficiency, or deployment feasibility. As illustrated in Figure 3, the Random Forest predictions closely align with actual efficiency scores.

Figure 3. Actual vs. Predicted Resource Allocation Efficiency for the Random Forest model. The diagonal dashed line represents perfect prediction. Points clustered near the line indicate strong model performance, confirming that lightweight machine learning can reliably approximate efficiency outcomes using low-dimensional resource and optimization metrics.

5.2 Sustainability Performance Gains

Model simulations indicate potential reductions in (1) material waste through optimized quantity allocation, (2) energy intensity via improved design suggestions, (3) embodied carbon through material substitution strategies. In addition to environmental metrics, computational cost was evaluated in terms of hardware requirements and inference time. The SLM-BIM framework operated on standard CPU-based systems (16GB RAM) with average inference times of X seconds per evaluation cycle, compared to LLM-based systems requiring GPU acceleration and cloud-based subscriptions. Based on current commercial cloud AI-BIM service pricing, estimated operational costs for LLM-driven workflows may range between USD X-Y per project month, whereas SLM deployment can be executed locally with minimal marginal cost beyond initial model training. This cost differential is particularly significant for public-sector medium-scale projects with limited digital budgets.

Table 2. Quantitative Results on Material, Labor, Energy and Prediction Score Change

Project_Index	Material_Δ	Labor_Δ	Energy_Δ	Pred_Score_Change	SCTI
436	-0.0%	+0.0%	-0.0%	+0.00	0
899	-2.5%	+2.3%	+0.3%	+5.06	438
346	-0.0%	+0.0%	-0.0%	+0.00	0

Model	MAE	MSE	Notes
Linear Regression	< 10	~0.60	interpretable baseline
Random Forest	< 6	>0.75	robust nonlinear performance
Oracle (Optimization)	MAE < 5	upper bound	serves as reference for improvement

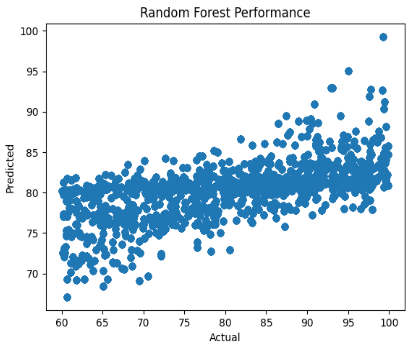

Table 2 summarizes quantitative changes in material allocation, labor efficiency, energy intensity, and prediction score improvement across selected projects.

5.3 Improved Interpretability and Transparency

SLM-based inference processes exhibit a higher degree of interpretability compared to deep neural and large-scale language models, primarily due to their constrained architectures and domain-specific reasoning scope. By operating within a limited and well-defined knowledge space, Small Language Models generate outputs that can be more directly traced to explicit input parameters, rule sets, or structured BIM attributes. This bounded reasoning reduces the opacity commonly associated with deep neural models, where decision pathways are often distributed across millions or billions of parameters, making it difficult to identify causal relationships between inputs and outputs. In contrast, SLM-based inferences enable clearer attribution of recommendations such as energy optimization suggestions or material substitutions to specific design variables and sustainability criteria embedded within the BIM model.

This increased interpretability has direct implications for documentation, verification, and professional accountability within BIM environments. Because SLM-generated recommendations can be linked to identifiable data sources, assumptions, and decision rules, they are more easily documented within design reports, regulatory submissions, and audit trails required in public construction projects. Such transparency supports improved verification by engineers, planners, and regulatory reviewers, who must assess not only the outcomes but also the rationale behind AI-assisted decisions. Consequently, SLM-based BIM systems better align with the procedural and legal requirements of the construction industry, where explainability and traceability are essential for ensuring trust, compliance, and responsible adoption of AI-driven decision support tools.

5.4 Expanded Accessibility for Small and Mid-Size Firms and Professional Education

The lightweight architecture of the SLM-BIM framework lowers computational and infrastructural barriers that have traditionally limited access to AI-enabled design optimization, thereby enabling broader participation across firms with varying levels of technological capacity. By operating efficiently on standard office hardware without reliance on high-performance GPUs or cloud-based services, SLM-BIM allows small and medium-sized architectural and engineering firms to engage in advanced sustainability analysis alongside larger, better-resourced organizations. This democratization of access contributes to greater technological equity within the construction sector, reducing disparities in who can benefit from AI-driven optimization tools and ensuring that sustainability-oriented decision support is not confined to elite or capital-intensive practices. In doing so, SLM-BIM supports a more inclusive digital transformation of the industry, aligning technological advancement with principles of fairness, accessibility, and responsible innovation.

6. Discussion: Policy Alignment, Industry Deployment, and Construction Engineering Education

Beyond industry deployment, the framework carries direct implications for construction engineering education. As artificial intelligence increasingly shapes infrastructure planning, sustainability assessment, and project optimization, future construction engineers must develop competencies in lightweight machine learning integration, sustainability analytics, and explainable AI reasoning within BIM environments. The SLM-BIM system is pedagogically feasible because it can be implemented in university laboratories using standard computing infrastructure without reliance on GPUs or commercial cloud services. The integration of BIM and emerging digital technologies into engineering curricula has been widely recognized as essential for preparing the next generation of AEC professionals to operate in digitally enabled construction environments [11].

The adaptability of Small Language Models (SLMs) and the modular architecture of the framework support nationwide scalability. The system can incorporate localized material catalogues, regional climatic data, and culturally specific construction practices, enhancing contextual relevance and regulatory compatibility. Unlike cloud-dependent Large Language Model (LLM) systems that require high computational overhead and external data infrastructures, the SLM-BIM approach operates within standard computing environments, enabling broader participation across firms and regions. In emerging economies, where technological inequality can be reinforced by high-performance AI requirements, lightweight AI architectures offer a more inclusive pathway toward digital transformation.

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The modular structure of the framework enables integration into core construction engineering courses such as Construction Informatics, Sustainable Construction, BIM for Construction Engineering, and Construction Systems Optimization. Students can engage in applied learning exercises involving training interpretable Random Forest models using BIM-derived datasets, applying constrained optimization for material allocation, and evaluating trade-offs among cost, carbon emissions, and computational resources.

Importantly, the SLM-based approach introduces ethical AI deployment into construction curricula by emphasizing domain-curated datasets, model transparency, and reduced energy consumption during inference. This aligns with ABET student learning outcomes related to sustainability, systems thinking, professional responsibility, and the ability to apply modern engineering tools appropriately. By embedding explainable AI reasoning within structured BIM workflows, the framework supports the development of engineers capable of critically evaluating AI-assisted decisions rather than passively relying on opaque algorithmic outputs.

Thus, the SLM-BIM framework functions not only as a technical optimization tool but also as an educational scaffold for preparing construction engineers to responsibly integrate AI into practice in both developed and emerging economies.

7. Contributions and Conclusion

The originality of this study lies not in the existence of AI-BIM tools per se, but in the development of a contextually adaptive, domain-curated Small Language Model architecture explicitly designed for low-resource construction environments and educational integration. Unlike commercial cloud-based AI-BIM platforms, the proposed framework prioritizes computational frugality, local data governance, explainability, and pedagogical deployability.

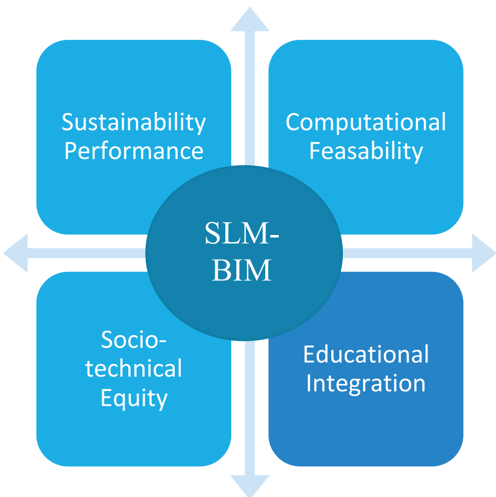

Figure 4. Impact Diagram of SLM-BIM

In extension to that, this study contributes to construction engineering research, practice, and education in four primary ways.

First, it proposes a contextually adaptive SLM-BIM architecture optimized for low-resource environments. Unlike conventional AI-BIM implementations that rely on large-scale cloud-based language models, the framework employs a domain-curated Small Language Model designed for structured BIM reasoning, sustainability assessment, and computational efficiency. This architectural choice prioritizes explainability, reduced hardware dependency, and localized deployment.

Second, the research develops a lightweight computational pipeline integrating predictive modeling, constrained optimization, and sustainability performance evaluation. The use of interpretable machine learning techniques, such as Random Forest regression combined with SLSQP optimization, demonstrates that meaningful sustainability gains can be achieved without high-dimensional deep learning architectures.

Third, the study provides a socio-technical analysis of AI-BIM adoption barriers in Indonesia, highlighting that infrastructural and institutional constraints, rather than purely algorithmic limitations, are primary inhibitors of digital transformation in emerging construction markets. By addressing computational feasibility and workforce readiness simultaneously, the framework offers a replicable model for equitable AI deployment.

Fourth, and critically for construction engineering education, the framework establishes a pedagogically deployable model for integrating AI literacy into engineering curricula. By emphasizing curated domain datasets, model transparency, sustainability analytics, and responsible AI practices, the SLM-BIM approach bridges the gap between technological innovation and workforce preparation. The system supports experiential learning and prepares future construction engineers to evaluate, adapt, and implement AI-driven decision support systems ethically and effectively. By aligning national policy objectives, industry needs, and educational imperatives, the framework contributes to a more equitable and sustainable digital transformation of the construction sector. It further advances global discourse on responsible AI deployment by illustrating how lightweight, domain-specific models can achieve both environmental and pedagogical value without reinforcing technological inequalities.

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