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ARTIFICIAL INTELLIGENCE BASED ESTIMATION OF OFFSITE PANEL REQUIREMENTS IN BUILDING CONSTRUCTION: CHALLENGES AND OPPORTUNITIES

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Abstract: The construction industry is increasingly adopting offsite panelised systems, particularly light gauge steel (LGS) panel solutions, as a means of improving productivity, reducing waste, and accelerating project delivery. However, a critical challenge remains in accurately determining the quantity of LGS panels and any supporting hot-rolled steel (HRS) requirements for a given building project in the early stages of tendering, design, and planning. Estimating LGS and HRS quantities involves complex interdependencies between architectural configurations, structural requirements, building typologies, and site-specific constraints. Traditional estimation methods, which rely heavily on expert judgement and manual quantification processes, are time-consuming, inconsistent, and prone to error, often resulting in procurement inefficiencies. Despite growing research on artificial intelligence (AI) and machine learning (ML) applications in construction, their specific application to offsite LGS panel quantity estimation remains largely unexplored. Data-driven approaches capable of processing multiple building parameters simultaneously are needed to generate reliable quantity predictions for early-stage decision-making. The presented research proposes a conceptual framework for applying AI and ML techniques to estimate LGS panel and HRS requirements for building projects. The framework identifies key input parameters including building geometry, floor area, storey height, structural system type, complexity, and opening ratios. A structured methodology is outlined encompassing data requirements, feature identification, model selection considerations, and validation approaches. The framework addresses implementation challenges including data scarcity in offsite construction, workflow integration, and interpretability of model outputs for industry practitioners. The proposed framework has the potential to improve the accuracy and efficiency of LGS and HRS quantity estimation, support better procurement planning, and reduce material wastage. This conceptual contribution, developed through a University College Dublin – Evolusion Innovation partnership, provides a structured foundation for future empirical studies and AI tool development in offsite construction.

Keywords: Offsite construction, panelised systems, artificial intelligence, machine learning, quantity estimation, LGS construction

1 INTRODUCTION

Pre-construction estimation of material requirements sits at the centre of the problem of uncertainty in the construction sector, and is seen in cost overruns, material miscalculations, and procurement inefficiencies remaining common across project types and geographies (Datta et al. 2024). Offsite construction improves predictability by manufacturing components in a controlled factory environment, with delivery methods classified under Categories 1–3 of the Modern Methods of Construction (MMC) framework (https://www.buildoffsite.com/content/uploads/2019/04/MMC-I-Pad-base_GOVUK-FINAL_SECURE-1.pdf). Light gauge steel (LGS) panelised systems, within Category 2, have gained traction as a delivery mechanism offering documented productivity gains and reductions in on-site waste (Narula 2025).

AI and ML models learn predictive relationships directly from data, accommodating nonlinear interactions that manual specification cannot capture; applications to construction cost, duration, and material prediction have expanded since 2020 (Chakraborty et al. 2020). Drawing on literature and Evolusion Innovation practitioner insights, this paper contributes (1) a structured AI framework, (2) key predictive features, and (3) implementation challenges for LGS estimation at tender stage.

2 BACKGROUND AND RESEARCH GAP

AI and ML have been increasingly applied across offsite production monitoring, scheduling, and cost modelling, including workstation time measurement (Rashid and Louis 2021), fabrication duration prediction (Mohsen et al. 2023), digital twins for panel production scheduling (Alsakka et al. 2024), and AI-based cost modelling for UK offsite housing (Serugga 2025). However, material quantity prediction remains the least-studied domain in construction AI. Beljkaš et al. (2020) estimated concrete and reinforcement consumption for bridges from geometric inputs using neural networks, with imprecision increasing at smaller dataset sizes. Venu Jaya et al. (2026) predicted off-cut waste from modular wall panel data, identifying material type and room count as dominant predictors, a feature set overlapping with the LGS panel problem. Table 1 maps traditional estimation limitations against ML opportunities. Each traditional approach constrains reliability at early project stages, whereas ML methods can learn from historical project data rather than depending on complete design documentation or expert judgement.

Table 1: Traditional estimation limitations and corresponding ML opportunities

Traditional approach	Key limitation	ML opportunity
Expert-based manual take-off	High inter-estimator variability; slow	Consistent, replicable predictions calibratable against outcomes
Parametric rules (panel per m²)	Fails to capture opening ratios and plan complexity	Learns nonlinear relationships across diverse geometries
Drawing-dependent quantification	Requires near-complete design documentation	Early-stage prediction from partial project descriptors
Cost-analogy from prior projects	Poor transfer across building typologies	Adapts to distributional variation given adequate training data

In practice, the data landscape across offsite projects is highly fragmented: some projects maintain structured BIM models, while others rely on PDF drawings requiring manual digitisation. This inconsistency presents a further challenge for ML models that require standardised training data.

Despite these advances in production monitoring, scheduling, and cost modelling, no study has specifically addressed the prediction of LGS panel and HRS quantities from early-stage building descriptors. This gap motivates the conceptual framework proposed in Section 3.

3 PROPOSED FRAMEWORK

Three categories of candidate input were identified from the literature: building geometry (floor area, plan dimensions, height), storey configuration, and building typology. Floor area is the most frequently adopted predictor in construction estimation (Chakraborty et al. 2020). Storey configuration shapes the vertical repetition of panel types and conditions manufacturing sequencing. Typology (residential, commercial, mixed-use) determines the architectural configurations and structural loadings from which LGS panel and HRS demand derives. Additional parameters such as structural system type, plan complexity, and opening ratios may further improve predictive performance as data availability increases. Output targets include LGS panel and HRS quantities expressed as linear metres and tonnage, each carrying distinct procurement implications. The conceptual framework is illustrated in Figure 1.

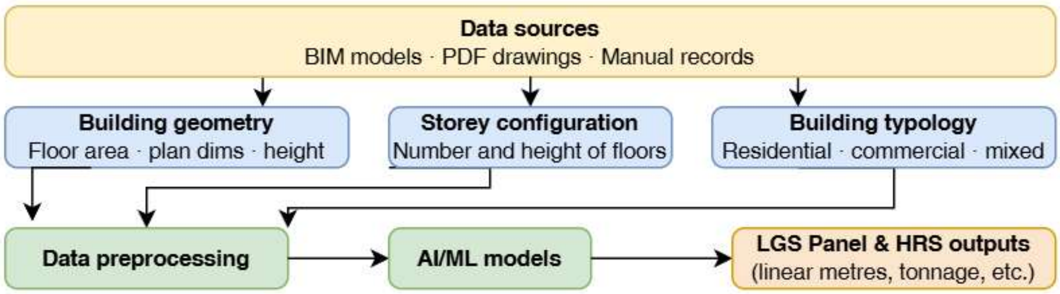

Figure 1: Conceptual framework for AI/ML-based LGS panel requirement estimation

Several ML method families warrant evaluation for this proposed framework. Tree-based ensemble methods have produced consistent results across material and cost prediction tasks in analogous contexts (Chakraborty et al. 2020; Venu Jaya et al. 2026); probabilistic regression methods offer uncertainty bounds alongside point predictions, a property of practical value in procurement settings; and regularised linear models may generalise more reliably than complex nonlinear architectures when training data is limited (Beljkaš et al. 2020). Method selection depends on dataset size, target distribution, and typological diversity. A comparative benchmarking approach across method families appears more appropriate than committing to a single architecture at this stage, while transfer learning may improve accuracy as the dataset grows (Oliveira et al. 2026). Validation encompasses cross-validation, hold-out testing, and post-hoc feature attribution to address interpretability, while probabilistic outputs and tendering-integrated design respond to procurement and workflow challenges.

4 CHALLENGES AND OPPORTUNITIES

Data scarcity was the most persistent constraint identified in this study and in practice. LGS panel layout data is held by manufacturers as proprietary operational records and, unlike general construction cost data, may not benefit from publicly accessible datasets. The industry partnership underpinning this research provides access to such records, though accumulating sufficient scale and typological diversity remains a multi-year undertaking. Mitigation strategies include BIM-based data augmentation and synthetic oversampling.

Workflow integration presents a second constraint. Embedding the tool within existing tendering workflows, rather than as a standalone application, likely conditions adoption more than predictive accuracy alone; usability, software compatibility, and interpretability are equally important for practitioner uptake (Serugga 2025). Since LGS quantity estimates feed directly into manufacturing capacity commitments, probabilistic outputs warrant consideration in model selection.

Accurate early-stage estimation reduces procurement exposure and material waste. Venu Jaya et al. (2026) demonstrated that predicted material waste could be linked to carbon cost calculations in modular construction, creating a pathway from quantity estimation to environmental impact quantification. From an AI and ML perspective, the data constraints identified in this project point toward model architectures that perform well under limited sample sizes, such as regularised models and tree-based ensembles.

5 CONCLUSION

A conceptual framework for AI/ML-based LGS panel estimation has been presented, with three candidate input categories and multiple ML method families warranting comparative evaluation. Data scarcity, workflow integration, and interpretability constitute the principal implementation challenges; transfer learning and BIM-based augmentation offer candidate mitigation approaches. The framework contributes a structured foundation for future empirical work and practical tool development within the offsite construction sector. This framework is currently being validated using real-world project datasets to improve the speed, accuracy and efficiency of LGS quantity estimation at tender stage.

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