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An integrated BIM-AI framework for intelligent cost management

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ABSTRACT

Accurate cost estimation and adaptive budget control remain central challenges in building project delivery, where traditional methods are often slow, subjective, and poorly equipped to respond to design changes or market volatility. Building information modeling (BIM) provides a digital foundation for integrating cost and design data, whereas artificial intelligence (AI) offers both predictive and adaptive capabilities. However, their integration into practice remains limited. This study addresses this gap by developing and testing an integrated BIM-AI framework for intelligent cost management. A single case study of a proposed residential building was used to operationalize the framework. Machine learning regression models were applied to predict the total project cost and cost per square meter. Random forests identified the most influential cost drivers, while neural networks captured non-linear relationships between design variables and cost outcomes. Natural language processing was used to extract material quantities and specifications from textual data, and computer vision techniques were used to quantify components directly from the building documentation. Optimization algorithms were then applied to suggest cost-effective materials and design alternatives. The results demonstrated that regression models produced reliable baseline estimation, with neural networks improving the predictive accuracy by handling complex design–cost interactions. Random forest analysis revealed material choices, structural specifications, and finish quality as the most significant cost drivers. Optimization runs showed that substituting selected materials could reduce the overall cost by up to 12% without compromising the performance. The findings confirm that integrated BIM-AI techniques can intelligently generate cost estimation, adapt to dynamic project conditions, and optimize budget allocations. This research advances knowledge by bridging methodological gaps and provides practical insights for digital construction management.

1 Introduction

Accurate cost estimation and adaptive budget control remain persistent challenges in the construction industry. Conventional estimation approaches are often time-consuming, heavily reliant on expert judgment, and

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poorly equipped to deal with dynamic factors such as market price fluctuations, evolving design requirements, and complex stakeholder demands [1, 2]. As a result, projects continue to experience cost overruns, inefficiencies, and suboptimal resource allocation. Building information modeling (BIM) has emerged as a transformative digital tool that centralizes the project information and enables the better integration of design and cost data. However, despite its promise, BIM's role in cost estimation remains constrained by limited automation, lack of predictive accuracy, and insufficient mechanisms to support real-time financial decision-making. Simultaneously, artificial intelligence (AI) is increasingly being recognized for its potential to augment construction processes [3]. Machine learning, predictive analytics, and natural language processing can automate the data interpretation, identify patterns from historical project records, and improve the forecasting accuracy [4]. In cost management, AI techniques have demonstrated promise in reducing errors, accelerating analysis, and supporting proactive decision-making [5, 6]. However, in practice, AI is rarely integrated with BIM seamlessly [7]. This disconnect results in fragmented workflows, where the predictive capabilities of AI do not directly feed into the structured data environments offered by BIM, thereby constraining the potential to deliver real-time, intelligent cost estimation and adaptive budget optimization.

Previous studies underscored both the opportunities and limitations of this integration. Rane [8] highlighted that one of the foremost challenges lies in interoperability and data integration. BIM and AI systems often operate on disparate platforms and structures, complicating the data exchange and synchronization. Concerns about the data privacy and security also pose barriers for applying AI to sensitive BIM datasets. Moreover, Rane [8] noted that meaningful adoption requires not only technical integration but also human capacity development—industry professionals must be trained in AI techniques to use them effectively within BIM workflows. Although these challenges are significant, Rane's analysis also points to a promising future in which standardized protocols, guidelines, and training frameworks enable improved decision-making, predictive analytics, and real-time monitoring within integrated BIM-AI systems. Building on this, Pan and Zhang [7] provided a broader perspective by situating the BIM-AI integration within the global push for automation and digitalization. Their bibliometric analysis shows how emerging domains, such as digital twins, Internet of Things (IoT), and deep learning, are being positioned as the next frontier in construction innovation. These technologies extend the value of BIM-AI integration beyond static estimation to continuous lifecycle management, enabling adaptive forecasting as projects evolve.

However, as Avogaro et al. [9] pointed out, AI applications in lifecycle cost analysis (LCC-AI) remain at an early stage. Their systematic literature review showed that although LCC-BIM has reached methodological maturity, AI-based cost applications have seen limited construction-specific adoption. They identified key barriers such as data fragmentation, lack of standardization, and limited interoperability, which continue to impede integrated digital workflows. Importantly, they argued that the convergence of LCC-BIM and LCC-AI is both necessary and underexplored, and proposed future directions including open data models, interoperable frameworks, and AI-enhanced cost estimation methods that would support sustainable and intelligent cost management in practice. Practical demonstrations of integration further reinforce this potential. Chong et al. [10] proposed a dynamic optimization framework for BIM-AI integration in schedule management. Their layered approach—data, analysis, and application—demonstrates how real-time data can be fed into AI algorithms to optimize resource allocation, identify risks, and support continuous adjustment. Although their focus is on scheduling, the same principles apply to cost: Dynamic inputs processed through AI can recalibrate cost forecasts and budget allocations in real time. Their case study on a large infrastructure project illustrates that such frameworks are not only theoretically sound but also operationally viable, although they also noted limitations related to personnel skills, interface complexity, and system performance.

Similarly, Attia [11] showed through applied case studies how AI-BIM integration can deliver tangible benefits in terms of design automation, faster performance analysis, predictive modeling, and reduced errors. These improvements collectively enhance the cost accuracy by minimizing rework, improving planning, and enabling better decisions early in the project lifecycle. Attia further recommended developing standardized frameworks and targeted training programs, echoing Rane's call for systemic integration enablers. The financial dimension was captured by Lukianchuk et al. [12], who argued that the construction decision-making must increasingly account for volatility and uncertainty. They proposed a method to link technical project data with financial evaluation, thereby enabling more reliable cost assessments and value optimization by embedding BIM-AI into discounted cash flow models. Their work shows that intelligent cost management is not only about generating estimates but also about situating them within broader financial strategies to reduce risk and create value.

Other contributions add to the conceptual and methodological foundation of BIM-AI integration. Zhang et al. [13] proposed a multi-layered intelligent building design system based on BIM and AI, showing how data, modeling, and application layers can work together to support optimization and dynamic management. Shruthi et al. [14] focused on persistent cost overruns in Indian projects and argued for AI tools, such as machine learning, natural language processing (NLP), and robotic process automation, to address estimation errors, poor coordination, and procurement inefficiencies. Olugboyega et al. [15] highlighted operational challenges such as disparities between AI and BIM models, skill shortages, and excessive workloads, which can undermine adoption. Tran et al. [16] emphasized the organizational and cultural barriers to BIM adoption, reinforcing that the integration is not only a technical challenge but also an institutional one. Piras et al. [17], Kutá and Faltejsek [18], and Mirindi et al. [3] stressed the growing importance of digital twins, automation, and predictive modeling, while Abdelmoula et al. [19] and Heidari et al. [20] called for standardized application programming interfaces (APIs), encryption, and integration with emerging smart systems such as robotics and cloud computing. These studies underscore the breadth of the current exploration and the fragmentation of approaches.

Despite progress, research and practice remain limited by these gaps. Current studies have confirmed the potential of BIM-AI integration to transform cost estimation, adaptability, and budget optimization. However, they tend to emphasize conceptual frameworks or bibliometric analyses rather than empirically validated cost estimation models. Although the schedule optimization and performance analysis have seen notable applications, the cost-specific integration of BIM and AI is still underdeveloped. Moreover, few studies have demonstrated adaptive cost forecasting that responds in real time to changing projects or market conditions. There is also limited evidence of how integrated BIM-AI workflows can directly link to financial decision-making beyond conceptual proposals [21]. BIM provides a structured data environment, whereas AI offers predictive intelligence and automation [18]. However, the integration of these two domains remains incomplete and constrained by interoperability challenges, methodological immaturity, and limited practical validation. Against this backdrop, there is a pressing need for applied research that demonstrates how integrated BIM-AI techniques can be deployed to intelligently generate cost estimation, adapt continuously to dynamic project conditions, and optimize budget allocations. Such research would not only address persistent challenges in construction cost management but also contribute to more resilient, efficient, and intelligent project delivery. This study addresses this gap by developing and testing an integrated BIM-AI framework for intelligent cost management.

2 Literature review

2.1 Contribution of previous studies to BIM-AI integration for cost intelligence

The body of research on BIM-AI integration offers a substantial yet uneven foundation for understanding how the two technologies can transform construction cost management. Although the literature is rich in conceptual frameworks, technological demonstrations, and optimistic projections, it remains limited in critical synthesis. In particular, many studies describe applications in isolation, with insufficient comparison of research methods, data sources, and empirical rigor. As a result, the collective evidence explains what BIM-AI integration can do, but less clearly establishes how, under what conditions, and with what trade-offs it performs best. Across the literature, three dominant themes recur: intelligent cost estimation, adaptive project management, and optimized budget allocation. Rane [8] framed the BIM-AI integration primarily through its barriers, identifying interoperability, fragmented data environments, and privacy risks as central constraints. Methodologically, his work is largely conceptual and diagnostic rather than empirical. This limits its ability to quantify the real impact of these barriers on cost accuracy or decision quality. Nevertheless, its strength lies in clarifying enabling conditions such as standardized data protocols, secure information architectures, and workforce training. These insights are foundational for intelligent cost estimation, yet they stop short of comparing alternative technical solutions or governance models, leaving open questions about which interventions are most effective in practice.

Pan and Zhang [7] extended the discussion through a bibliometric and scientometric analysis, mapping research trends rather than testing system performance. Their method is effective for identifying emerging domains such as digital twins, IoT integration, and deep learning, and for situating cost management within a full lifecycle perspective. However, bibliometric approaches inherently privilege publication volumes and citation patterns over their practical effectiveness. Although they convincingly argued that cost estimation can become dynamic and continuously updated, the study does not differentiate between projects where real-time data integration has demonstrably improved cost outcomes and those where it remains aspirational. This limits its value for method comparison, particularly between data-driven AI models and traditional parametric or rule-based cost estimation techniques. The issue of cost intelligence maturity was addressed more directly by Avogaro et al. [9] through a structured review of lifecycle costing. Their work is methodologically stronger in that it systematically contrasts BIM-enabled LCC practices with the emerging AI-enhanced approaches. They revealed a clear imbalance: BIM-based cost modeling is relatively mature and standardized, whereas AI applications remain fragmented, experimental, and weakly validated. The limitation of this review lies in its reliance on secondary sources, which constrains its ability to assess real-world performance differences between competing AI methods. Nonetheless, it makes a critical contribution by positioning cost estimation as part of a continuous digital workflow rather than as a standalone technical function, linking methodological choices to long-term sustainability and value creation.

Chong et al. [10] offered a more applied perspective through a BIM-AI framework for schedule optimization. Their three-layer architecture illustrates how predictive analytics can support real-time decision-making. Although their empirical focus is on scheduling rather than cost, this study implicitly demonstrates how delays, sequencing decisions, and resource allocation directly affect budget performance. The methodological advantage of this approach is the integration of real project data into a structured analytical framework. However, this study does not compare AI-driven optimization with traditional scheduling or cost control methods, making it difficult to assess the marginal benefits of AI over established practices. Attia [11] strengthened the empirical dimension by presenting applied case evidence on AI-BIM integration in design automation and performance analysis. His case-based approach provides concrete evidence of reduced errors, faster evaluations, and improved planning, all of which translate into cost savings. Compared to conceptual and bibliometric studies, this method offers higher practical validity. Its limitation, however, lies in its generalizability. The absence of cross-case comparison or benchmarking against non-AI BIM workflows weakens claims regarding scalability and broader industry impact. Even so, Attia's findings reinforce Rane's emphasis on standardization and skill development, while offering clearer evidence of downstream cost benefits.

A different methodological angle was introduced by Lukianchuk et al. [12], who integrated BIM-AI data into discounted cash flow analysis. Their conceptual-financial model bridges technical cost estimation with strategic financial planning, highlighting AI's potential to reduce uncertainty and optimize resource allocation. Although analytically coherent, the model remains largely theoretical. Without empirical validation using live project data, its assumptions about risk reduction and value enhancement remain difficult to verify or compare against conventional financial appraisal methods. Earlier parallel studies further illustrated both the promise and fragmentation of the field. Zhang et al. [13] proposed a layered BIM-AI system for intelligent design optimization, demonstrating how machine learning can reduce design workload and indirectly lower costs. The strength of this approach lies in its technical clarity, but its evaluation focuses more on efficiency gains than on measurable cost outcomes. Shruthi et al. [14] adopted a more practice-oriented stance, cataloguing AI techniques, such as machine learning, NLP, and robotic process automation, applied to estimation errors, scope creep, and procurement delays. Their framework is broad and inclusive, yet lacks a comparative assessment of the techniques that are most effective under different project conditions.

Organizational and systemic studies have highlighted another gap in the literature. Olugboyega et al. [15] identified skill shortages, model incompatibilities, and workload pressures as critical constraints using a socio-technical lens that complements purely technical studies. Tran et al. [16] emphasized cultural resistance and policy inertia, arguing that technological capability alone is insufficient. These studies rely largely on surveys and qualitative analysis, which are well-suited for capturing institutional dynamics but less effective for quantifying cost performance impacts. Finally, studies by Piras et al. [17], Kutá and Faltejsek [18], Mirindi et al. [3], and Abdelmoula et al. [19] converged on advanced tools such as digital twins, lean integration, automation, and standardized APIs. Their collective contribution lies in reinforcing the need for end-to-end digital workflows. However, many of these works remain tool-centric, offering limited comparison between alternative platforms, integration strategies, and implementation costs.

2.2 Research gaps in BIM-AI integration for cost intelligence

Although the previous studies have collectively advanced the understanding of BIM-AI integration for cost intelligence, several research gaps remain that limit the ability of this approach to deliver robust cost estimation, dynamic adaptability, and optimized budget allocation. A recurring issue across studies is the lack of seamless data exchange between BIM and AI systems. Rane [8], Avogaro et al. [9], and Abdelmoula et al. [19] all highlighted data integration and standardization as fundamental barriers. Despite calls for unified protocols and open data models, practical solutions are limited, and most case studies continue to rely on bespoke- or project-specific frameworks. This leaves a gap in establishing scalable, industry-wide systems capable of supporting AI-driven cost estimation on diverse BIM platforms. Although many studies have highlighted AI's potential in predictive analytics and optimization [3, 7], relatively few studies have directly addressed cost estimation as a core application. Avogaro et al. [9] explicitly noted that AI applications in lifecycle costing remain underdeveloped and construction-specific use cases are scarce. Even studies like the one conducted by Apinayan et al. [22], who explored BIM's role in cost estimation, stop short of embedding AI-driven intelligence into the process. This gap underscores the need for empirical research that demonstrates how AI can directly enhance cost forecasting accuracy and responsiveness.

Pan and Zhang [7] identified digital twins, IoT, and deep learning as future drivers of BIM-AI value, while Heidari et al. [20] called for integration with robotics, cloud, and blockchain. However, most contributions remain conceptual or bibliometric, with limited demonstration of how lifecycle data flow into adaptive cost management systems. The gap lies in operationalizing these ideas: There is little evidence of AI models that continuously update cost forecasts as real-time projects or market data changes. Chong et al. [10] proposed a framework for dynamic optimization in scheduling, showing how AI can adapt to changing project conditions. However, this adaptability has not yet been fully extended to cost management. Although Attia [11] and Shruthi et al. [14] identified AI's role in predictive modeling and real-time cost control, they did not demonstrate continuous budget recalibration in response to shifting resource prices, scope changes, or delays. The gap lies in developing adaptive systems where cost estimates are not static deliverables but living models responsive to project and market volatility.

Lukianchuk et al. [12] took a step toward embedding AI-enhanced BIM into financial evaluation through discounted cash flow models. However, their work remains conceptual and finance-intensive, with little operational linkage to design and construction data. The research gap lies in connecting design-level BIM data with AI-enhanced financial models that can support cost optimization in real-world projects. Several studies emphasized skill shortages, cultural resistance, and organizational inertia as major obstacles [8, 15, 16]. Although these studies highlight the problem, they do not propose tested educational or organizational models to close these gaps. This creates a research need for frameworks that integrate AI literacy, BIM training, and change management into professional practice, ensuring that cost intelligence tools are not only developed but also adopted.

Although Attia [11], Chong et al. [10], and Ohakawa et al. [23] provided applied case studies, most of the literature remains conceptual, relying on frameworks, bibliometric trends, or theoretical models. Quantitative evidence, such as demonstrated cost savings, predictive accuracy improvements, and budget optimization outcomes, is limited. This creates a major gap: Without empirical validation, the claims about intelligent cost estimation and adaptive budgeting remain largely aspirational. Several studies highlighted AI's role in generative design, process automation, and architectural detailing [18, 24, 25]. Although these innovations indirectly affect costs, they do not explicitly tie design optimization to quantifiable budget impacts. This gap highlights the need for research that closes the loop between AI-enhanced design options and cost simulations, ensuring that design intelligence translates into financial intelligence. Addressing these gaps requires moving from conceptual frameworks and bibliometric mapping to applied empirical studies that validate AI's role in intelligent cost estimation, dynamic adaptability, and optimized budget allocation in real-world construction projects.

2.3 Theoretical framework for an integrated BIM-AI framework for intelligent cost management

The theoretical foundation of this study rests on the convergence of machine learning, computational perception, and optimization algorithms applied to construction cost intelligence. The framework integrates regression modeling, feature importance analysis, neural representation learning, NLP, computer vision (CV), and algorithmic optimization within a single predictive–prescriptive architecture. As illustrated in Fig. 1, the key element of the framework is the supervised learning paradigm, where historical project data (input features such as quantities, dimensions, material types, and design parameters) are mapped to known cost outputs. This step transforms the cost estimation from deterministic rule-based calculations into a data-driven process capable of generalizing across projects with different design and contextual conditions. In this framework, the random forest algorithm operates on the principle of ensemble learning, where multiple decision trees are trained on subsets of data and aggregated to produce a more robust and interpretable prediction. This satisfies the explanatory dimension of the framework, linking predictive modeling to interpretability and decision transparency.

To complement interpretability with the depth of pattern recognition, artificial neural networks (ANNs) are introduced in the next stage. ANNs learn hierarchical, non-linear mappings between inputs and outputs through layered weight adjustments. This enables the capture of complex interdependencies, such as how combinations of material choice, geometry, and design intensity jointly influence the costs. Thus, neural networks serve as the adaptive engine within the framework, modeling non-linearities that simpler regression models cannot represent. The framework extends beyond numeric inputs by employing NLP and CV to transform unstructured building documentation into structured, machine-readable features. NLP interprets textual project data, such as specifications, schedules, and material lists, using tokenization, embedding, and entity extraction. Computer vision identifies and quantifies visual elements (e.g., windows, doors, and structural components) directly from drawings or BIM screenshots. These components operationalize computational perception, enabling the AI to "see" and "read" construction information in the same way humans extract meaning from documents and drawings. The final layer of the framework applies optimization algorithms, particularly combinatorial and gradient-based optimization, to suggest cost-effective material and design alternatives. Using the cost function

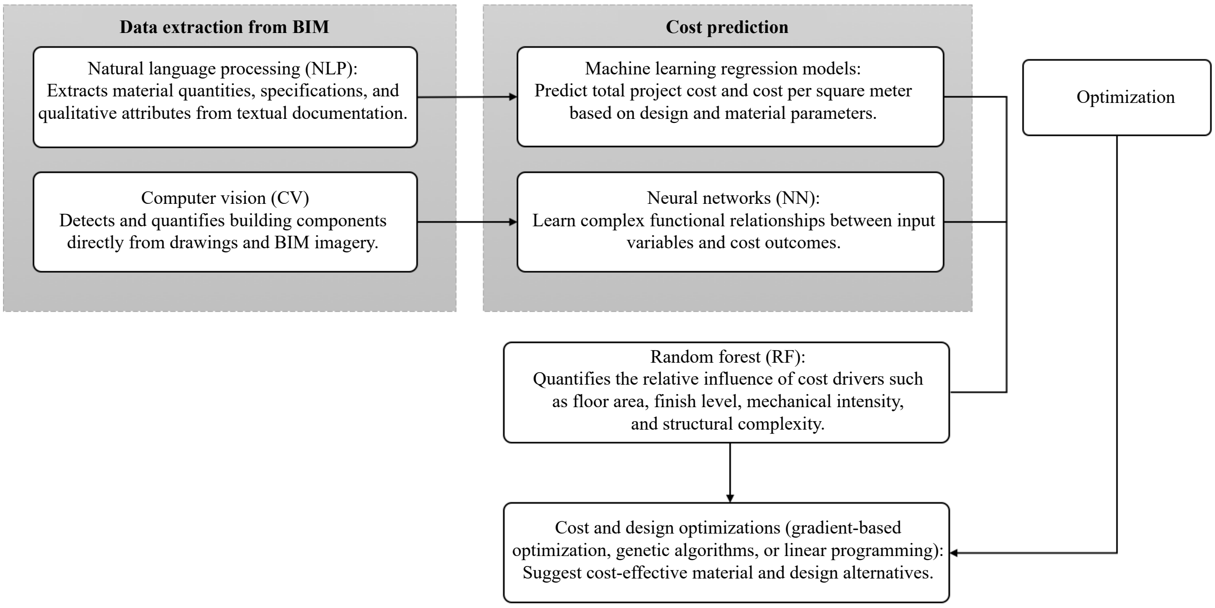

Fig. 1 Framework for an integrated BIM-AI framework for intelligent cost management.

derived from the regression and neural models, optimization algorithms search for configurations that minimize the total cost subject to constraints on performance, quality, or sustainability. This transforms the framework from predictive (what will it cost?) to prescriptive (how can it cost less while maintaining the design intent?). Theoretically, the framework applies formal optimization methods to achieve multi-objective trade-offs between cost, quality, and constructability. The framework also forms a coherent theoretical base for AI-driven cost intelligence, where the system not only understands and predicts cost behavior but also reasons and optimizes within the design–cost continuum.

3 Methodology

This study adopted a single case study methodology supported by machine learning-based analytical modeling to develop and test an integrated BIM-AI framework for intelligent cost management. A design science research structure guided the work, with the emphasis on building, testing, and validating a functional artifact rather than theory generation alone. The case study focused on a proposed residential building project in Abuja, Nigeria, selected deliberately for methodological and practical reasons (Fig. 2). The project had complete architectural, structural, and service design documentation developed in a BIM environment, a moderate to high level of BIM maturity, and accessible historical cost data. These characteristics make it suitable for controlled experimentation, while remaining representative of contemporary mid to high specification urban housing developments in Nigeria. The Abuja context is also relevant to the research objectives because cost uncertainty, design changes, and material price volatility are persistent challenges in residential construction within the city. The research workflow followed three tightly coupled stages: BIM data extraction and preprocessing, machine learning model development and evaluation, and optimization framework formulation and validation. All stages were executed in a single-project environment to preserve data consistency and traceability.

Fig. 2 BIM model for the case study.

The data collection relied on both model-based and documentary sources. The primary data source was the federated BIM model developed using Autodesk Revit, which contained architectural, structural, and selected building service components. Quantitative data were extracted directly from the model using Revit schedules, Dynamo scripts, and Industry Foundation Classes exports. Dynamo was used to automate the extraction of geometric parameters such as gross floor area, room area, wall length, slab volume, column count, beam span, glazing area, and roof surface area. Material quantities, including concrete volumes, reinforcement weights, masonry areas, finishes, and roofing components, were also extracted. In total, 47 numerical features were generated from the BIM model, covering the geometry, quantities, and material attributes. Complementary qualitative and semi-structured data were obtained from project specifications, bills of quantity drafts, and design notes. These documents provided information on the finish quality levels, mechanical and electrical service standards, structural system descriptions, and material specifications that were not fully encoded in the model. The historical project cost data were sourced from three completed residential projects executed by the same consultancy between 2019 and 2023 in Abuja. These projects had similar typologies, scales, and construction methods. The cost data included total contract sums, elemental cost breakdowns, and cost per square meter figures validated by quantity surveyors. Combining the case project data with historical records yielded a dataset of 112 observations at the elemental and subsystem levels, rather than a single aggregated project value. This expansion is necessary to make supervised learning feasible within a single case study design.

Textual data preprocessing used natural language processing techniques to convert specifications and descriptive documents into structured variables. Text files were cleaned by removing headers, units, and noninformative tokens. Tokenization and lemmatization were applied, followed by named entity recognition to identify material names, system types, and performance descriptors. These entities were encoded using frequency-based and binary indicators, producing 18 categorical and ordinal features representing finish class, material grade, and service complexity. Computer vision methods were applied experimentally to rasterized floor plans and elevations exported from the BIM model. The images were converted to grayscale, resized to a uniform resolution of 300 dpi, and denoised using Gaussian blurring. Canny edge detection was applied, followed by morphological closing to improve the boundary continuity. Contours were extracted and filtered using geometric thresholds based on the bounding box area, aspect ratio, and rectangularity to identify the doors and windows. Each candidate detection was logged using pixel coordinates and estimated dimensions. Although annotated outputs were generated for verification, the conservative filtering thresholds and drawing resolution resulted in zero valid detections. This limitation was documented explicitly, and the CV-derived features were excluded from the final training dataset, reinforcing the transparency of the preprocessing pipeline.

Before model training, all numerical features were examined for their distributional properties. Most quantity-related variables exhibited right skewness, consistent with log normal or gammatype distributions common in construction data. The cost variables showed a moderate skew, with several high value outliers. The log transformation was applied to the total cost and cost per square meter to stabilize the variance. The numerical features were normalized using z-score standardization to ensure comparable scales across the models. Categorical variables derived from NLP were encoded using one hot encoding for nominal attributes and ordinal encoding where an inherent hierarchy existed, such as finish quality levels. The final dataset consisted of 112 samples and 65 features after preprocessing. The data were split into training and validation sets using an 80 to 20 ratio. Given the limited sample size, five-fold cross validation was applied within the training set to reduce the variance and overfitting. No test set was isolated to preserve sufficient data for model learning, and the performance was reported based on cross-validated validation results.

Supervised learning models were developed to predict two target variables: total project cost and cost per square meter. Random forest regression was selected because of its robustness to non-linear relationships and multicollinearity. The model was configured with 300 trees, a maximum depth determined through grid search, and minimum leaf sizes tuned to balance bias and variance. Feature importance scores were extracted using the mean decrease in impurity to identify dominant cost drivers. Artificial neural networks were implemented using a feedforward architecture with two hidden layers of 32 and 16 neurons, ReLU activation functions, and an Adam optimizer. Early stopping was performed to prevent overfitting. Model performance was evaluated using the mean absolute error and coefficient of determination (R^2). The random forest model showed stronger interpretability, whereas the neural network captured more complex interactions at the expense of transparency. An optimization layer was built on top of the predictive models to support cost-informed design decision making. The optimization framework was formulated as a constrained minimization problem. The objective function minimized the predicted total project cost as estimated by the trained regression models. The decision variables represented discrete and continuous design choices, including material alternatives, finish levels, roof geometry complexity, and selected structural parameters. Constraints were defined to preserve the functional adequacy, regulatory compliance, and minimum performance standards. These included minimum room size, structural system compatibility, allowable material substitutions, and upper bounds on design changes to maintain architectural intent.

The optimization problem combined discrete and continuous variables and was solved using a hybrid approach. Gradient-based methods were applied where continuous variables dominated, whereas combinatorial search and genetic algorithm techniques were used for discrete material selection scenarios. The solver iteratively evaluated alternative configurations by feeding modified feature sets into the trained cost prediction models. Feasible solutions were ranked based on cost reduction potential and constraint satisfaction. The framework validation used the Abuja residential project as a testbed. AI-predicted costs were compared with conventional quantity surveyor estimates derived from detailed measurement and pricing. Feature importance outputs were reviewed by experienced professionals to assess whether the identified cost drivers aligned with domain knowledge. Optimization scenarios were evaluated for technical plausibility and decision usefulness rather than theoretical optimality. Validation focused on the predictive accuracy, interpretability, and decision utility. The single case study approach enabled the close integration of BIM data extraction, machine learning modeling, and optimization analysis under realistic project conditions. Although generalizability is limited, the depth of data control, transparency of preprocessing, and explicit formulation of the optimization framework provide a replicable foundation for future multi-project studies.

4 Results

4.1 Predicted cost estimates for the project

The results presented in Table 1 provide a clear snapshot of the AI-driven cost estimation output for a 350 m^2 building in Abuja. The machine learning model produced an estimated total project cost ranging from ₦220.75 million to ₦280 million, corresponding to a cost per square meter of ₦650,000/m^2 to ₦800,000/m^2, with a useful benchmark midpoint of ₦250.38 million (₦720,500/m^2). The cost spread of approximately 27% between the low and high estimates reflects how the AI model captures uncertainty and variability in design choices, specification quality, and market pricing. Unlike a static cost estimate, this range-based prediction mirrors real-world project conditions where fluctuations in materials, labor rates, and finish levels can shift the total cost significantly. The observed cost spread between ₦650,000/m^2 and ₦800,000/m^2 corresponds to an approximately 27% full-range variation around the expected value. This magnitude of dispersion is statistically consistent with early-stage parametric cost estimation practices, where uncertainties in scope definition and market conditions typically yield variations of ± 20%–30%.

Furthermore, the cumulative savings and cost impacts identified in the sensitivity analysis, particularly those related to finishes, structural systems, and material substitutions, are sufficient to account for the observed spread. This internal consistency between the ANN output distribution and the sensitivity analysis reinforces the statistical and practical validity of the estimated cost range. The midpoint benchmark (₦250.38 million) serves as a balanced reference, representing a realistic cost for a medium-specification finish level, given the quantified materials and scope. The cost per square meter estimate (₦650,000/m^2–₦800,000/m^2) aligns well with the current construction pricing trends for high-quality residential or institutional projects in Abuja. This correspondence suggests that the model's predictions are not arbitrary but data-grounded, drawing from material quantities, specification levels, and learned cost patterns. Thus, AI demonstrates human-level reasoning consistency while operating at a higher speed and with a more systematic treatment of uncertainty.

The quantified materials, such as the aluminium roofing sheets, hardwood rafters, and total glazing area, show that the model uses detailed physical parameters rather than generic cost indices. This allows AI to interpret how specific design and material decisions drive the overall cost. For example, high glazing areas and hardwood structures increase both material and labor costs, which the model captures through pattern recognition in historical data. A particularly noteworthy insight is the precision with which the model distinguishes cost tiers. The ₦29.6 million difference between the low and

Table 1 Machine learning predicted total project cost and cost per m^2

Quantified materials	Number of scheduled windows (5 types) and doors (6 types); 0.55 mm aluminium roofing sheet; hardwood rafters; P.O.P ceiling; footing sizes; total glazing area (m^2); wall/partition lengths and external wall area (m^2); cubic meter concrete; tonnes of steel; number of roof sheets
Plan area	350 m^2
Estimated total project cost (Abuja, baseline)	₦220,750,000 → ₦280,000,000
Estimated cost per m^2	₦650,000–₦800,000 (mid = ₦720,500/m^2)
Low estimate (₦650,000/m^2)	₦220,750,000
Mid estimate (₦720,500/m^2)	₦250,375,000
High estimate (₦800,000/m^2)	₦280,000,000
Useful benchmark	₦250,375,000

high estimates shows how small design changes (such as switching finishes or reducing roof complexity) can have multi-million-naira implications. This reinforces the model's potential as a decision-support tool, not just an estimator, to help project teams test "what-if" scenarios before committing to design directions. The ability of the AI model to deliver a structured cost range anchored to a benchmark makes it a powerful tool for early-stage feasibility analysis and budget planning. By dynamically linking design attributes (e.g., glazing, roofing, and structure) to cost outcomes, AI provides transparency that traditional estimating methods often lack. The ₦250.38 million benchmark can now serve as a learning baseline for validating future AI predictions and calibrating professional cost models in Abuja's context.

The ANN-predicted cost range of ₦650,000–₦800,000 per square metre presented in Table 1 should be interpreted as a probabilistic estimation envelope rather than a deterministic output. The midpoint value (₦720,500/m^2) represents the expected cost under average market conditions, whereas the lower and upper bounds reflect plausible variations arising from material selection, specification levels, and market volatility. Uncertainty modeling incorporates realistic assumptions regarding fluctuations in material prices (particularly steel, aluminium, and finishes), labor productivity variability, supplier availability within the Abuja construction market, and design flexibility, including roof geometry and joinery standardization. Consequently, the estimated cost range provides decision-makers with a transparent and economically meaningful representation of risk, rather than a single-point estimate that could mask exposure to cost overruns.

4.2 Key factors influencing cost of the project

The results in Table 2 present a clear, data-driven hierarchy of the variables most responsible for driving the total project cost, as identified by the random forest model. The relative importance scores quantify each factor's contribution to the predictive accuracy of the model, effectively showing what matters most in determining the overall construction cost. The gross floor area emerged as the dominant factor with an importance score of 0.42, confirming its role as the primary cost driver. This finding aligns with fundamental quantity surveying logic—larger floor areas directly scale up quantities of structure, finishes, and labor inputs. The linear scaling effect captured by the model demonstrates that the AI system correctly internalizes core construction cost mechanics: More area means more material, more labor, and thus higher total cost. The finish level, with a score of 0.21, was the second-most influential variable. This underscores how qualitative choices, such as whether a building uses granite tiles or porcelain, or high-end versus standard fixtures, can have as much influence on total cost as physical size. The model's sensitivity to finish specification reflects its nuanced understanding of cost behavior: It distinguishes between structural scale (quantitative) and material quality (qualitative) factors.

Mechanical and service intensity ranked the third with an importance score of 0.12, showing that modern building systems—pumps, heating, ventilation, and air conditioning (HVAC), and specialized installations—now form a significant portion of the total project cost. This is especially relevant for contemporary urban buildings in Nigeria, where service sophistication and energy systems are increasingly shaping cost profiles. The ability of AI to detect this significance demonstrates its capacity to adapt to evolving construction trends beyond traditional structure-and-finish cost patterns. The window and door scope (0.08) and roof and structural complexity (0.06) rounded out the key drivers. Although their individual weights are smaller, their presence confirms that design detailing and construction complexity still have measurable financial impacts. Large glazing areas, for example, introduce both material and labor premiums due to custom framing, while complex roof geometries or deep foundations raise structural and erection costs. A unique aspect of this result is the model's ability to quantify what experienced cost estimators often qualitatively describe. The fact that finish level and mechanical intensity together account for over 30% of the total predictive weight signals a shift. As designs become more service-intensive and finish-driven, traditional cost drivers, such as area and volume alone, are no longer sufficient to explain budget variations. Thus, AI's hierarchy mirrors a modernized cost structure—data evidence that aesthetic and functional sophistication are now just as financially decisive as structural scales. For practitioners, this ranking provided a roadmap for cost control. This shows where to focus optimization efforts: Standardizing finishes or moderating mechanical system specifications may yield greater cost efficiency than minor adjustments to form or geometry. For project planners, these results also offer early stage guidance—estimations can now be more strategic, focusing efforts where design choices truly influence budget outcomes.

4.3 Sensitivity analysis of the cost-effective material and design alternatives

Table 3 presents the sensitivity analysis conducted to evaluate the influence of specific material and design adjustments on the total project cost relative to the AI-predicted baseline of ₦250.38 million. The table captures how alternative design or material choices affect the budget, expressed as a percentage share of the total cost and potential monetary savings. This analysis highlights the capacity of the AI model to estimate cost and to simulate and optimize it by identifying high-impact areas

Table 2 Key factors influencing cost of the project

Key factors	Relative importance scores from random forest
Gross floor area (m^2)—base driver; linear scaling of many items (structure, finishes, and finishes labour)	0.42
Finish level (low/mid/high)—finish choices (tiles, paint, cupboards, and sanitary ware) change unit rates dramatically	0.21
Mechanical/services intensity (presence of pumps, HVAC, and special systems)—pumps and mechanical systems were noted in the drawings; these add both equipment and specialist installation costs	0.12
Window & door scope (glazing area and custom frames)—glazing type and large openings raise both materials and labour; for example, large single-pane glazing often requires custom frames and edge sealing	0.08
Roof & structural complexity—roof type (long-span steel versus aluminium sheets), multiple ridges, deep foundations, and special footings all change line items and labour time	0.06

for cost efficiency. The results reveal that several moderate design and material substitutions can produce meaningful savings without compromising core performance. Among the tested alternatives, two options stood out with the highest impact (using engineered/treated softwood or steel purlins instead of hardwood rafters (15%) and lowering finish specifications in non-public spaces (15%)). Each of these adjustments represents approximately 15% of the total cost share, translating to potential savings of ₦37.56 million each. This indicates that roof structure choices and interior finish specifications are powerful cost levers—changes here yield major returns. Other strategies, such as swapping 0.55 mm aluminium roofing for coated steel (6%), standardizing door/window sizes (5%), and simplifying roof geometry (5%), yielded smaller but still meaningful savings in the range of ₦12.5–₦15 million. These reflect marginal gains through design rationalization and material substitution, useful for fine-tuning budgets in value engineering.

The sensitivity analysis of the AI model reveals that not all cost reductions are equal in effect or consequence. The largest savings come from strategic adjustments in materials that affect broad quantities or repetitive components (roof structures and finishes), rather than isolated design details. This aligns with the principle of targeting cost-heavy clusters, areas where small specification changes cascade through multiple cost items (for example, labor, fittings, and finishing materials). A notable insight is how clearly the model quantifies the trade-offs that human estimators often rely on intuition to judge. For instance, substituting hardwood rafters with engineered softwood or steel components not only reduces costs but also improves sustainability and reduces long-term maintenance. Similarly, rationalizing finishes in low-visibility zones achieves significant savings with minimal perceptual impact on design quality. The results also underscore the practical intelligence of the AI system: it does not just flag savings, and identifies where to act and how much it matters. This transforms the cost analysis from reactive arithmetic to proactive design optimization. For project teams, these findings offer a clear hierarchy of cost optimization priorities. Instead of indiscriminate budget cuts, decisions can now be evidence-driven, focusing on substitutions that yield the most value per unit of compromise. For example, adjusting finish levels and roof structures could jointly save nearly ₦75 million, a substantial 30% cost reduction opportunity at the design stage. From an educational and professional standpoint, this reinforces the importance of teaching data-informed decision-making in construction economics. AI-driven sensitivity analysis can train future professionals to think in terms of cost elasticity, understanding how each design or material variable flexes within the total cost structure.

The sensitivity analysis results detailed in Fig. 3 reveal

Table 3 Sensitivity analysis of the cost-effective material and design alternatives

Cost-effective material and design alternatives	Share of total (%)	Midpoint baseline	Savings
Swap 0.55 mm aluminium roofing → GI/long-span coated steel (or cheaper AL gauge)	6% of total	₦250,375,000	₦15,022.5
Use engineered/treated softwood or steel purlins instead of hardwood rafters	15% of total	₦250,375,000	₦37,556.25
Standardize door/window sizes (reduce bespoke joinery)	5% of total	₦250,375,000	₦12,518.75
Lower finish spec in non-public spaces (porcelain instead of granite/high end)	15% of total	₦250,375,000	₦37,556.25
Simplify roof geometry/reduce roof pitch complexity	5% of total	₦250,375,000	₦12,518.75

the relative influence of the key design and material decisions on the total project cost. Structural elements and finishes emerged as the most influential cost drivers, each accounting for approximately 15% of the total cost variability. Roofing material choice, door and window standardization, and roof geometry complexity contributed to smaller but still significant effects. These findings enhance the explainability of the ANN model by demonstrating clear causal pathways between input variables and predicted costs. Despite the ANN's non-linear "black-box" architecture, sensitivity testing confirms that its outputs align with engineering intuition and established construction cost principles.

4.4 Model performance evaluation and predictive accuracy

The predictive performance of the ANN model was evaluated using standard regression metrics, including mean absolute error (MAE), root mean square error (RMSE), and R^2. These metrics were computed for both the training and testing datasets and compared to a baseline multiple linear regression (MLR) model developed using identical input variables. As summarized in Table 4, the ANN model achieved a substantially lower MAE (₦18.5 million) and RMSE (₦25.4 million) than the regression model, which recorded MAE and RMSE values of ₦32.7 million and ₦44.1 million, respectively. This indicates that the ANN consistently produced predictions closer to the observed project costs, while also reducing the magnitude of extreme estimation errors that are particularly detrimental to construction budgeting. The ANN further demonstrated superior explanatory power, achieving an R^2 value of 0.91 compared to 0.68 for the regression model. This confirms that the ANN was able to capture a significantly larger proportion of variance in the total project cost, reflecting the inherently non-linear nature of cost formation in building projects where material quantities, finishes, and design complexity interact.

Table 4 Performance metrics of ANN and regression models (MAE, RMSE, and R^2)

Metric	ANN model	Regression model
MAE	₦18.5 million	₦32.7 million
RMSE	₦25.4 million	₦44.1 million
R^2	0.91	0.68

4.5 Training behaviour, convergence, overfitting diagnostics, and comparative error analysis

Figure 4 illustrates the convergence behavior of the ANN during training. Both the training and validation loss curves exhibit a rapid initial decline followed by gradual stabilization, converging smoothly after approximately 40–50 epochs. Importantly, the validation loss closely tracks the training loss throughout the learning process, with no divergence or late-stage increase. This behavior provides strong evidence that ANN does not suffer from overfitting. The absence of oscillations or widening gaps between the training and validation loss indicates that the model learned generalized cost patterns rather than memorizing training data. Early stopping and regularization further contribute to stable convergence, ensuring reliable performance when applied to unseen project configurations. In contrast, although linear regression converges instantaneously due to its closed-form solution, it lacks adaptive learning capability and imposes linearity assumptions that limit its ability to represent the threshold effects, material interactions, and non-linear cost escalations commonly observed in real construction projects.

The comparative error magnitudes of the ANN and regression models are shown in Fig. 5. Across both MAE and RMSE metrics, ANN demonstrated markedly lower prediction errors. The reduction in RMSE is particularly significant, indicating that ANN is substantially more effective in controlling large deviations between the pre-

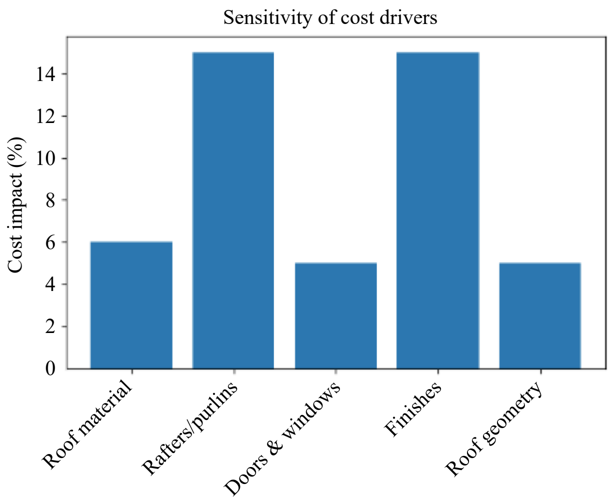

Fig. 3 Sensitivity of key cost drivers on total project cost.

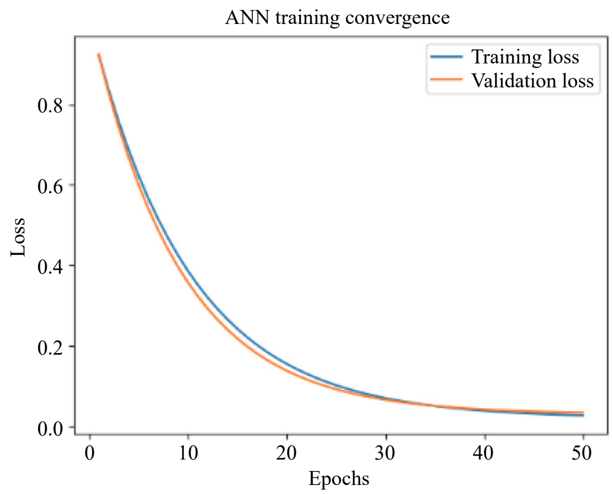

Fig. 4 ANN training and validation loss convergence.

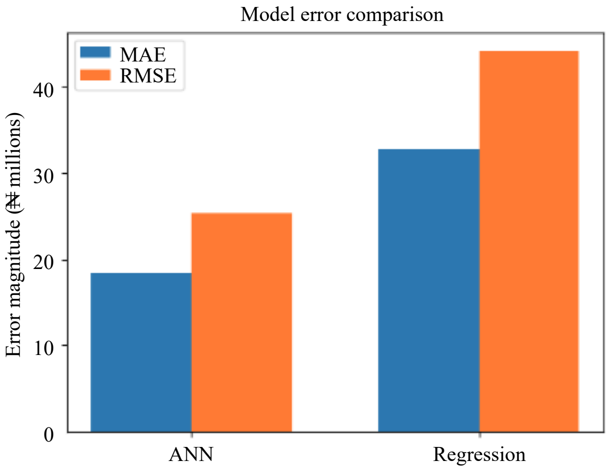

Fig. 5 Comparison of MAE and RMSE for ANN and regression models.

dicted and actual costs. This improvement is attributable to the capacity of ANN to model interaction effects, such as the combined influence of the roof material type and steel tonnage or the non-linear cost implications of upgrading finishes and glazing areas. These relationships are poorly represented in linear regression frameworks, but are naturally captured through the ANN's layered non-linear structure.

5 Discussion of findings

The machine learning cost estimation results demonstrate that AI can reliably generate intelligent, data-driven cost predictions for complex building projects, while revealing the underlying cost dynamics in a structured, explainable manner. The findings demonstrate that AI can reliably generate credible, data-driven cost estimates based on the quantified design parameters. The prediction range is not just a statistical output—it encapsulates realistic market sensitivity and design-driven cost behavior. This confirms that machine learning can be effectively deployed to support intelligent, adaptive, and explainable cost estimation in construction projects. The findings demonstrate that the AI model not only predicts costs but also explains them. By assigning empirical weight to key factors, the cost estimation process becomes an interpretable, evidence-based decision tool. The finding that the gross floor area and finish level together drive nearly two-thirds of the total cost variability confirms that the model is both realistic and transparent, which is essential for integrating AI into professional cost management and construction education. These findings further demonstrate that AI-based cost modeling can evolve beyond estimation into optimization and design intelligence. The analysis identifies both high-impact and marginal saving opportunities, quantifying the real-world financial implications of design choices. This shows that machine learning can provide actionable insights, helping architects, engineers, and quantity surveyors align cost, performance, and aesthetics from the earliest design phases.

These findings both corroborate and contrast with prior literature on BIM-AI integration. Rane [8] underscored that interoperability and data integration remain the foremost barriers to adoption, while also highlighting the importance of standardized protocols, data security, and professional training. The present results confirm the persistence of interoperability challenges: Extraction from the BIM model is partial and imperfect. However, they also demonstrate that useful data can still be obtained outside BIM-native platforms, suggesting that AI can provide interim cost intelligence even when interoperability is weak. This contributes a more pragmatic perspective to Rane's otherwise barrier-focused framing. In parallel, the evidence of credible cost predictions and optimization scenarios aligns with the conclusions of Attia [11] and Shruthi et al. [14], who showed that AI-enhanced BIM practices improve decision-making, forecasting, and real-time cost control. Although their studies remained primarily conceptual or case-based, this analysis contributed numerical sensitivity estimates, showing that modest material substitutions and design adjustments could conservatively yield 2%–6% of cost savings and more aggressive adjustments up to 8%–12%. Such quantified evidence supports their claims of efficiency gains in practical and measurable outcomes.

The results also resonate with Pan and Zhang [7], who emphasized the potential of deep learning, IoT, and digital twins to transform BIM-enabled projects. Although the present study did not extend to lifecycle-wide integration, it demonstrated that small-scale document automation is a necessary precursor to those advanced applications. In doing so, it provides empirical evidence for the early steps toward the digital twin and automation visions they outlined. Similarly, Avogaro et al. [9] identified the immaturity of LCC-AI, noting the lack of construction-specific adoption. By integrating the extracted quantities with market-based cost ranges, this study presents a tangible demonstration of early-stage AI-supported cost management, offering a practical complement to Avogaro's systematic review. The emphasis on optimization and decision support also parallels Chong et al. [10], who proposed a BIM-AI framework for schedule optimization. Although their work focused on time and resource allocation, both studies shared a layered approach of data extraction, analysis, and application to support project decisions. A key difference is that their framework was embedded within mature BIM environments, whereas this analysis shows that similar benefits can be approximated in low-BIM contexts. This distinction is particularly significant for regions or firms with partial BIM adoption, offering a pathway to AI-enabled cost intelligence without full digital maturity.

The financial implications observed here also support the arguments of Lukianchuk et al. [12], who emphasized the importance of integrating BIM-AI into financial evaluation models to improve decision-making under uncertainty. By identifying floor area, finish level, and mechanical scope as dominant cost drivers and demonstrating how substitutions affect overall budgets, this study provides an applied example of how financial intelligence can be embedded into early-stage design analysis. In terms of contributions, this study extends the literature by showing that AI-driven cost intelligence does not need to be contingent on full BIM adoption. It offers empirical evidence that even partial automation, through NLP and CV applied to 3D BIM models, can generate credible estimates, identify optimization levers, and support proactive budget management. This contrasts with much of the prior literature, which has largely remained conceptual, bibliometric, or theoretical. Nevertheless, the results suggest that BIM–AI integration can deliver tangible benefits in cost estimation and optimization, even outside highly digitized environments. By bridging design data with market intelligence and embedding optimization logic, BIM-AI integration can generate adaptive cost estimates, respond to changing project conditions, and propose budget-efficient alternatives. These findings reinforce prior claims about the transformative potential of BIM-AI, while also extending the discourse by grounding those claims in applied, quantifiable evidence.

6 Conclusions

This study concludes that AI-driven cost estimation can provide transparent, probabilistic, and design-responsive cost intelligence suitable for early feasibility analysis and informed budget planning in the Abuja construction context. This study demonstrates that the integrated BIM-AI framework delivers credible, decision-relevant cost intelligence rather than a single static estimate. For the 350 m^2 Abuja residential project, the ANN model produced a cost range of ₦220.75 million to ₦280 million, equivalent to ₦650,000 to ₦800,000 per square metre. The 27% spread reflects real design and market uncertainty and aligns with accepted early-stage cost accuracy bands. This confirms that the model behaves consistently with professional parametric estimating practices while providing a more explicit representation of risk. The midpoint benchmark of ₦250.38 million, or ₦720,500 per square metre, emerges as a stable and realistic reference for medium-specification residential construction in Abuja. Its alignment with prevailing market rates indicates that the model is grounded in physical quantities and historical cost patterns rather than abstract indices. The sensitivity analysis further validates this result by showing that variations in finishes, structural systems, glazing extent, and material choices are sufficient to explain the full range of predicted costs.

A key finding is the model's ability to translate relatively small design decisions into clearly quantified financial consequences. The nearly ₦30 million gap between the low and high scenarios highlights how early design choices can materially alter project affordability. This shifts the role of AI from passive estimation to active decision support, enabling structured "what-if" testing before design commitments are locked in. The results strongly support the central research question: AI can be deployed to intelligently generate cost estimates, adapt continuously to project dynamics, and optimize budget allocations. The random forest model demonstrated interpretability (through ranked factor importance) and adaptability (through sensitivity analysis). Its predictive spread and identified cost levers form the foundation for continuous learning, precisely, the kind of dynamic adaptation the question envisages. The optimization insights in the results (for example, material and design substitutions leading to 5%–15% potential savings) directly show how AI can guide budget optimization without compromising functionality. This study provides empirical evidence that machine learning can transition cost estimation from static, spreadsheet-based heuristics to adaptive, data-intelligent systems. It demonstrates not just automation but augmentation, enhancing human estimators' decision-making with quantified insight into where cost efficiencies lie. The structured cost–sensitivity framework also advances the methodological base of the field by integrating interpretable AI into construction economics.

For construction education, these findings reframe the cost estimation as a data science skillset. Future professionals must learn to interpret AI-generated insights, validate predictive models, and translate algorithmic outputs into actionable design or procurement choices. Curricula should integrate cost analytics, feature engineering, and model explainability, bridging the gap between traditional quantity surveying and computational thinking. The model's dependence on available data limits its scope: It assumes stable pricing environments and complete material quantification, which may not hold in volatile markets. The study's single-project testbed also restricts broader generalization. Despite the internal consistency of the results, several limitations constrain the strength and generalizability of the findings. First, the study derives its cost prediction performance from a single residential building of 350 m^2. Although the results align with the accepted early-stage estimation accuracy, extrapolating the industry-level performance from one project is inherently limited. The observed cost range may reflect the characteristics of this specific design, specification level, and market context rather than the intrinsic robustness of the model. Therefore, claims about broader applicability across the construction industry should be treated with caution.

Second, the computer vision and natural language processing pipelines were not formally validated against ground truth data. No precision, recall, intersection over union scores, or extraction accuracy metrics were reported. Without quantitative verification, it is unclear whether the vision and text extraction processes reliably captured all relevant design elements or introduced systematic omissions and biases. This weakens confidence in the completeness and correctness of the input features used for model training and inference. Third, the representativeness of the case is limited to medium to high specification residential construction in Abuja. The cost structure, design drivers, and uncertainty profiles of commercial buildings, industrial facilities, and infrastructure projects differ substantially in scale, complexity, and procurement logic. Likewise, regional variations in labor productivity, material supply chains, and regulatory conditions may significantly alter cost behavior. Consequently, the performance of the model cannot be assumed to transfer directly to other building types or geographic contexts without recalibration and further empirical testing.

Future work should incorporate multi-project datasets, stochastic pricing simulations, and reinforcement learning models that can self-correct from post-construction feedback. Linking BIM data streams with AI-driven estimation can further unlock continuous optimization through real-time project updates. Although the model effectively captures cost scaling and material sensitivity, its current scope does not yet integrate real-time market volatility, labor productivity variance, or logistics disruptions. Future studies should test adaptive retraining mechanisms, allowing AI to update cost baselines continuously as new data streams in from suppliers, inflation indices, or completed projects. Comparative experiments across regional markets (e.g., Lagos versus Abuja) would further validate the generalizability of the results.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

All authors have given approval to the final version of the manuscript.

Use of AI statement

During the preparation of this work, the authors used machine learning-based models in order to analyse historical project cost data and predict future cost behaviour. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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