eng

MDPI

Article

Digital Twins and AI Decision Models: Advancing Cost Modelling in Off-Site Construction

Joas Serugga

Department for Engineering and Built Environment, Birmingham City University, Birmingham B4 7RJ, UK; joas.serugga@bcu.ac.uk

Abstract: The rising demand for housing continues to outpace traditional construction processes, highlighting the need for innovative, efficient, and sustainable delivery models. Off-site construction (OSC) has emerged as a promising alternative, offering faster project timelines and enhanced cost management. However, current research on cost models for OSC, particularly in automating material take-offs and optimising cost performance, remains limited. This study addresses this gap by proposing a new cost model integrating Digital Twin (DT) technology and AI-driven decision models for modular housing in the UK. The research explores the role of DTs in enhancing cost estimation and decision-making processes. By leveraging DTs and AI, the proposed model evaluates the impact of emergent technologies on cost performance, material efficiency, and sustainability across social, environmental, and economic dimensions. As proposed, this integrated approach enables a cost model tailored for OSC systems, providing a data-driven foundation for cost optimisation and material take-offs. The study's findings highlight the potential of combining DTs and AI decision models to enhance cost modelling in modular construction, offering new capabilities to support sustainable and performance-driven housing delivery. The paper introduces a dynamic, data-driven cost model integrating real-time data acquisition through DTs and AI-powered predictive analytics. This dynamic approach enhances cost accuracy, reduces lifecycle cost variability, and supports adaptive decision-making throughout the OSC project lifecycle.

Keywords: utility theory; artificial intelligence; cost modelling; digital twins offsite construction

check for updates

Academic Editors: Juvenal Rodriguez-Resendiz, Akos Odry, José Manuel Álvarez-Alvarado and Marco Antonio Aceves-Fernandez

Received: 27 December 2024
Revised: 20 January 2025
Accepted: 21 January 2025
Published: 22 January 2025

Citation: Serugga, J. Digital Twins and AI Decision Models: Advancing Cost Modelling in Off-Site Construction. *Eng* **2025**, *6*, 22. https://doi.org/10.3390/eng6020022

1. Introduction

The demand for housing that delivers exceptional performance from design to lifecycle continues to grow [1–3], with stakeholders emphasising the need for speed, cost-efficiency, and adaptability [4]. Housing delivery must balance these demands while meeting lifecycle cost expectations [5], making cost performance—during initial construction and throughout a building's lifecycle—a critical focus. Off-site construction (OSC), particularly modularisation, has emerged as a promising solution to these challenges, addressing cost, time efficiency, and adaptability issues [6,7].

Modularisation leverages standardisation and repeatability to streamline construction processes and support efficient, cost-effective delivery [6,8]. However, achieving this efficiency often conflicts with the growing demand for individualised spaces, challenging developers to balance customisation with the benefits of modular design [9]. Moreover, the reliance on traditional costing processes, such as manual material take-offs, adds inefficiencies that hinder the potential of OSC systems [10].

To address these challenges, new methods are needed to enable cost-focused housing delivery while maintaining flexibility and adaptability [11,12]. Modularisation offers significant potential in processes and product development [8,13]. Process modularisation decouples activities in time, enabling more efficient scheduling and placing and distributing tasks across multiple locations for optimised workflows [14]. Product modularisation, conversely, decouples components within a system, facilitating interchangeability, upgrades, and adaptability in designs [15]. Product modularity enhances cost and process optimisation opportunities by reducing interdependencies among on-site processes [14,15].

Therefore, the interplay between product and process modularity creates a foundation for cost-efficient construction systems. Automated cost analysis and material take-offs are particularly crucial in modular systems, providing the flexibility to accommodate project performance variations while optimising lifecycle cost performance [16]. When integrated with emerging technologies, modular or unit-based costing systems can meet the increasing performance expectations of housing throughout its lifecycle [17].

This paper focuses on advancing cost modelling in OSC by integrating DTs and AI decision models. These technologies present enabling opportunities for enhanced cost analysis, providing real-time insights into material use, process optimisation, and lifecycle performance.

Current Challenges

Current approaches to modularisation in off-site construction rely heavily on standardisation, which often conflicts with the growing demand for bespoke designs that cater to individual user preferences [18]. This creates a trade-off where repetitive, standardised units optimise cost and efficiency but limit design flexibility and personalisation, challenging the balance between affordability and individuality [19].

To address this tension, modularisation must evolve to support more adaptable and flexible systems. A potential solution lies in decomposing designs into modular units of interchangeable components. These modular components would maintain compatibility through standardised interfaces, allowing for independent replacement, upgrades, and customisation without disrupting the overall system [20]. This approach supports lifecycle cost optimisation by enabling more efficient off-site preassembly and streamlining cost analyses and material take-offs.

In traditional OSC systems, cost analyses and material take-offs often remain cumbersome and inefficient, particularly for complex projects with numerous interdependent components and interfaces [16]. The reliance on bespoke designs results in thousands of interconnected yet distinct components, complicating cost estimations and increasing the risk of cost overruns [21]. Furthermore, it is arguable that manual decomposition of products and processes leads to suboptimal workflows that scale poorly with increasing project complexity, creating challenges for adaptability, future upgrades, and lifecycle management.

The proposed integration of DTs and AI decision models addresses these challenges by introducing automated and adaptive cost-modelling frameworks [22,23]. DTs provide real-time data on component behaviour, process optimisation, and lifecycle performance [22], while AI enhances the ability to analyse and predict cost impacts across multiple project variables [23]. Together, these technologies can enable the development of modular, unit-based costing models that streamline cost estimation and material take-offs.

This approach resolves inefficiencies in traditional systems by simplifying component interfaces, enabling automated cost analyses, and facilitating adaptability for future modifications [24]. The research, therefore, aims to address the following research objectives:

1. To develop a modular cost analysis model that integrates DTs for real-time monitoring and lifecycle cost optimisation.

2. To leverage AI decision models for automating material take-offs and enhancing cost prediction accuracy.
3. To evaluate the proposed framework through UK modular housing case studies and demonstrate its potential to address inefficiencies while supporting adaptability and sustainability in OSC systems.

Through integrating these advanced technologies, this research proposes a framework that optimises cost performance and meets the increasing demands for customisation and lifecycle efficiency in off-site construction, ultimately paving the way for sustainable and adaptive housing delivery.

2. Literature Review

2.1. Modular Housing Systems

Research such as Xue, Zhang, Su, Wu, and Yang [10] continues to highlight the increasing attraction of OSC methodologies as a modern approach that addresses time efficiency, cost management, and sustainability challenges. By shifting a substantial portion of construction activities to controlled factory environments, OSC minimises on-site complexities, enhances quality control, and reduces construction timelines as Blackenfelt [15] and Hussein et al. [25] separately highlighted. Among the various OSC methods, modular construction has emerged as a key strategy, emphasising the design and fabrication of standardised units or modules assembled on-site to create complete structures [6,18,20]. This approach offers several advantages, including scalability, adaptability, and cost savings [6,13].

2.1.1. Cost Modelling in OSC and Modular Construction

Cost modelling is a critical aspect of OSC, as it underpins decision-making processes related to budgeting, resource allocation, and project planning [10]. Unlike traditional construction, which often relies on bespoke designs and on-site labour-intensive processes, modular construction seeks to streamline cost estimation through standardised processes and repeatable components, according to authors such as Bayliss and Bergin [17], Hsu et al. [26], and Hussein and Zayed [6]. However, this standardisation introduces unique cost modelling challenges, as highlighted in studies such as Mao et al. [27], including the following:

1. Complex Interfaces: Modular construction involves numerous interfaces between components, increasing the complexity of cost estimation and lifecycle analysis that ultimately hinders its broader appeal, as argued in Pan et al. [28].
2. Customisation vs. Standardisation: The balance between customisation for user preferences and the cost-efficiency of standardised modules complicates the cost modelling process [29].
3. Lifecycle Considerations: Cost models ought to consider not only initial construction costs but also lifecycle costs, including maintenance, upgrades, and eventual decommissioning [30,31].

Traditional cost modelling approaches, which rely on manual calculations and static assumptions, struggle to keep pace with OSC projects' dynamic and interconnected nature, as highlighted in the review by Serugga et al. [32]. The authors add that manual material take-offs and cost analyses can be time-consuming and prone to error, particularly in complex projects with numerous modules and interfaces.

2.1.2. Emerging Trends in Cost Modelling

Advancements in technology have begun to reshape cost modelling in modular construction [32,33]. Building Information Modelling (BIM), according to authors such as Huynh and Nguyen-Ky [34] and Akbarieh, Jayasinghe, Waldmannm and Teferle [5], among others, has introduced opportunities for better data management, visualisation, and stakeholder collaboration. However, BIM alone is insufficient to address the growing need for real-time data integration and decision support [35].

DTs offer a more comprehensive solution by providing real-time, dynamic representations of physical assets, enabling continuous monitoring and optimisation of costs throughout a project's lifecycle [22]. Meanwhile, AI techniques, such as machine learning (ML) and predictive analytics, enhance the ability to automate material take-offs, predict cost impacts, and identify inefficiencies [36]. The integration of these technologies represents a paradigm shift in cost modelling, enabling more accurate, adaptive, and efficient processes.

2.2. Digital Twins in Construction: Current Applications and Potential

DTs have emerged as transformative tools in the construction industry, offering a dynamic and data-driven approach to project design, execution, and lifecycle management [37,38]. According to Batty [37], a Digital Twin is a virtual representation of a physical asset, system, or process continuously updating and evolving through real-time data integration from sensors, IoT devices, and other data sources. By bridging the physical and digital worlds, DTs enable construction professionals to monitor, analyse, and optimise construction processes and building performance across all project phases, as highlighted in the Omrany et al. [39] review.

DTs are being increasingly adopted in the Architecture, Engineering, and Construction (AEC) sector, with applications spanning various stages of the construction lifecycle such as in design [40], project implementation [41], and operations [42] among others. In design and planning, DTs simulate and visualise complex designs, enabling stakeholders to identify potential issues and optimise solutions before construction commences [38–40]. DTs are also integral and complementary in project processes, with BIM enhancing data accuracy and collaboration among multidisciplinary teams, as a review by Deng et al. [43] highlights. In the construction phase, on the other hand, DTs enable real-time monitoring of construction activities, allowing for better coordination and scheduling [39,42]. DTs can similarly assist in tracking the assembly of prefabricated modules in OSC, ensuring alignment with design specifications, according to research by Jiang et al. [44]. A review by van Dinter et al. [45] and a study by You et al. [46] also highlight DTs' role in predictive maintenance and quality control, supported by real-time data from sensors and IoT devices. At the same time, Drobnyi et al. [47], in their review, draw out DTs' capacity in the operations and maintenance stages to help facility managers monitor building performance, predict maintenance needs, and optimise energy usage. This emergent research shows that DTs are integral in lifecycle cost analysis that is enhanced by continuous data collection, allowing for informed decision-making regarding upgrades and retrofits [40,43,46,47]. Lastly, a study by Purcell et al. [48] focuses on DTs' role in sustainability and resilience processes, where they can support the assessment of the environmental impact of processes and their design, such as in energy use and carbon emissions, while their critical role in planning for resilience, enabling simulations of natural disasters or extreme weather scenarios, is investigated by research such as Ye et al. [49].

Therefore, in the OSC context, DTs hold promise for addressing challenges related to modularisation, cost modelling, and lifecycle management [39,41,42,46]. DTs can be the basis for real-time insights into material usage, labour requirements, and overall cost performance in enhanced cost modelling, as highlighted by Omrany, Al-Obaidi, Husain, and Ghaffarianhoseini [39]. At the same time, they present the opportunity to support dynamic updates, enable automated and ultimately accurate material take-offs, and reduce the potential for errors and cost overruns [50]. In process design and optimisation, integrating DTs with OSC systems promises to facilitate better planning and coordination of modular assembly and on-site installation, help identify production bottlenecks, and guide subsequent process improvements. In lifecycle design, DTs extend beyond initial construction to monitor the performance of modular components and the full envelope throughout their lifecycle, as demonstrated in the IT capabilities by Canedo [51]. This enables more accurate lifecycle cost analysis and supports adaptive reuse or recycling of modules. In mass customisation and adaptive design, DTs allow for greater flexibility in modular design, balancing customisation with cost and efficiency by simulating various configurations and scenarios, as evidenced in the study by Aheleroff et al. [52].

While the potential of DTs in construction is evident, several challenges warrant further exploration. One is the need to understand the extent and limits of integrating DTs with existing OSC workflows and technologies, such as BIM and AI, which often require substantial investment and skill sets, which is currently an area of limited research. Similarly, real-time data and processing can be resource-intensive, presenting potential challenges, particularly for large-scale projects [53]. Lastly, the continuing lack of standardised protocols for data exchange between physical and digital systems presents headwinds in the interoperability of the various capabilities.

2.3. AI in Cost Modelling Decision-Making

AI has become a critical tool in enhancing decision-making and cost analysis in many industries, including construction [36]. By leveraging techniques such as machine learning (ML), neural networks, and optimisation algorithms, AI enables more accurate predictions, real-time data processing, and adaptive systems that respond to project complexities [54,55]. In the context of OSC, AI provides significant potential for improving cost modelling, materials planning, and lifecycle analysis [56].

Some recent applications of AI in decision-making for OSC have included areas in predictive cost modelling where AI-powered models help predict project costs by analysing historical data, material prices [36], labour [57], and project-specific variables [58]. ML algorithms identify patterns and correlations that traditional methods may overlook [59], enabling more precise cost estimates. Other applications have been seen in material take-off and optimisation [36], demonstrating the potential for automating material take-off processes by analysing 3D models (e.g., BIM) and generating accurate quantities for procurement. Optimisation algorithms can suggest material substitutions or sourcing strategies to reduce costs [60]. In Lifecycle Cost Analysis (LCCA), on the other hand, AI has been shown to facilitate LCCA by simulating the performance of key components and processes over time and incorporating factors such as maintenance, energy usage, and depreciation [61]. This presents opportunities for more informed decisions about design and material choices. In decision-making, AI-driven Decision Support Systems (DSS) provide real-time recommendations based on project data [62]. For example, reinforcement learning algorithms can continuously adapt to changing conditions, dynamically [63], allowing opportunities to optimise schedules and cost performance. Lastly, in project risk management, AI capabilities can assess risks related to cost overruns, delays, and resource constraints [64]. Probabilistic models, such as Monte Carlo simulations, evaluate various scenarios [65] and, ultimately, their cost implications.

Foundations in AI for Cost Analysis

AI-based cost analysis and modelling can use multilinear regression predictions such as those adopted in Ghali et al.'s study [66]. In this study, the research was able to use two AI-based models: adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN), together with a linear model (multilinear regression analysis (MLR) for the prediction of costs (C) based on a set of independent variables (X_i), such as material quantities or labour hours, which can be predicted using the equation below:

$$C = \beta_0 + \sum_{i=1}^{n} (\beta_{\mathrm{i}} X_{\mathrm{i}}) + \varepsilon \tag{1}$$

where β_0 is the intercept, β_i are the coefficients for the variables, and ϵ the error term.

In terms of neural networks for complex cost estimation, Bode [67] demonstrates their applicability through classifying data and approximating functions in a sample data set (curve fitting). Using this method, approximate nonlinear cost functions by learning weights (W) and biases (b) to minimise the error (E) between predicted (C_{Pred}) and actual costs (C_{Actual}) can be found using the following computation:

$$E = \left(\frac{1}{n}\right) \sum_{i=1}^{n} \left(C_{actual,i} - C_{pred,i}\right)^2 \tag{2}$$

Neural networks are particularly effective at capturing complex relationships in large datasets, such as interdependencies between modular components [67,68].

Optimisation algorithms for cost minimisation, on the other hand, for example, in linear programming or multi-objective genetic algorithms, usually work in complement [69], to help AI to minimise costs while meeting project constraints $G(x) \leq 0$ following that $Minimise: \ f(x) \ Subject \ to \ G(x) \leq 0$, where $f(x)$ represents the total cost function and $G(x)$ includes constraints such as budget, time, and material availability. Bayesian networks, on the other hand, can quantify the probability of risks such as cost overruns [70]; given various risk factors R_i in the form $P\ (Cost\ Overun | R_1,\ R_2,\ \ldots\ldots.,\ R_n)$. Through this relationship, these networks support decision-making by identifying critical risk factors and their impacts on project costs [70].

While DTs offer dynamic, real-time data capabilities, their application in cost modelling remains yet to be fully leveraged [71]. At the same time, inadequacies in the automation of costing processes mean that traditional methods for material take-offs and cost estimation, which are labour-intensive and prone to errors, continue to encumber processes [72].

LCCA, on the other hand, is critical for OSC, given its reliance on modular components with extended usability and adaptability, but it continues to be deficient, as highlighted in the review by Zhou et al. [73]. LCCA models continue to fail to incorporate predictive and real-time insights from DTs or the adaptive capabilities of AI for long-term decision-making [74]. Finally, there is a continuing need to understand the complexity of managing modular designs that balance standardisation with the need for tailored user needs that require advanced decision-making frameworks [29]. The potential of AI and DTs to dynamically manage these trade-offs presents opportunities for new theories.

Emergent research into the complementary capabilities of DTs and AI for OSC cost modelling, although disjointed, currently points to benefits such as dynamic cost modelling with real-time updates, where DTs provide continuous data streams from sensors, IoT devices, and project management systems, which AI algorithms can process, to adjust cost models following the rule dynamically $C_{real-time} = f(C_{base}, D_t, U_t)$, where $C_{real-time}$ is the updated cost model, C_{base} is the initial cost estimate, and D_t and U_t are the real-time design and production changes and real-time utilisation and resource constraints, respectively. Similarly, AI-driven predictive models can use historical and real-time data from DTs to forecast future costs and maintenance needs for enhanced predictive analytics for lifecycle costs $C_{lifecycle}$ via Equation (3) as below:

$$C_{lifecycle\_} = \sum_{i=1}^{n} (P_i \cdot M_i) \quad (3)$$

where P_i and M_i are the probability of a specific maintenance event and the cost of the maintenance event, respectively.

Combined DT-AI systems can also help optimise modular component interfaces, balancing cost, performance, and adaptability [56]. AI optimisation techniques can evaluate multiple configurations to minimise total cost C_{total} via the rule $Minimise:\ C_{total} = C_{modules} + C_{assembly} + C_{lifecycle}$ taking into account the costs for modules, assembly, and lifecycle costs. Finally, AI can integrate user preferences and project constraints into decision models, enabling customised modular designs without sacrificing efficiency [62,63,75]. A utility function (U) can quantify trade-offs between cost (C), customisation (S), and lifecycle performance (L) via the rule $U = \alpha_1 C^{-1} + \alpha_s S + \alpha_3 L$, with $\alpha_1,\ \alpha_2$, and α_3 being the weight factors representing various project requirements priorities.

3. Methodology

This study employs an exploratory research framework to investigate the integration of DTs and AI decision models for advancing cost modelling in OSC. The exploratory approach is well-suited for identifying potential applications, challenges, and solutions and provides a testing bed for the integrated capabilities. The methodology combines qualitative and quantitative methods, case studies, and technology implementation to develop and validate a proposed cost modelling framework.

The research follows a structured approach to exploring the potential of DT and AI technologies in modular cost modelling, first through a comprehensive review of existing studies on OSC, cost modelling, DTs, and AI to identify research gaps and theoretical underpinnings. A model that integrates DTs and AI decision models is developed to automate cost analysis and material take-offs. A brainstorming exercise was conducted to contextualise OSC systems and explore opportunities for integrating advanced cost modelling technologies. This exercise focused on an OSC systems manufacturer based in the Midlands, U.K., specialising in modular housing systems. Two brainstorming sessions were held with a panel of eight experts selected to provide diverse perspectives on modular construction and its costing processes, ultimately informing initial contextual influences to gross floor area (GFA)-based costing. The panel included two experts in housing design and delivery, two experts in modular systems manufacturing, two experts in cost analysis for OSC, and two representatives from contractors experienced in implementing modular construction projects.

The choice of experts ensured a broad yet experienced panel, with participants selected for their expertise and decision-making roles in OSC-related processes. During the sessions, a conceptual cost modelling framework was presented to elicit feedback on its appropriateness, completeness, and practical applicability. Experts provided insights on improving the model, particularly regarding its integration with modular manufacturing and construction workflows.

After brainstorming sessions, the conceptual model was evaluated against two modular home case studies. These case studies provided a practical context to test the framework's effectiveness and validity. Based on the findings from the brainstorming sessions and case study evaluations, a revised cost modelling framework was developed, presented, and discussed in this research. The model is evaluated in a case study, evaluating its effectiveness and efficiency compared to traditional methods.

3.1. The Case Studies

Two modular housing designs, a two-bedroom and a three-bedroom configuration, were selected as case studies to evaluate and validate the key concepts of the proposed cost modelling framework. These homes were developed for a major housing group in the Midlands, U.K., with the requirements management process collaboratively overseen by the manufacturers and architects. Constraints related to modular manufacturing, transportation, and construction were iteratively identified and addressed during the design process.

The modular setup for the three-bedroom homes is illustrated in Figures 1 and 2. At the same time, the dimensions for various spaces in both designs are summarised in Table X. The structural framework of the homes is primarily steel, with hot and cold-rolled sections used depending on material availability. The manufacturing company operates at a capacity of producing one module per day, employing an integrated process that includes technical design, planning approval, mechanical and electrical (M&E) installations, roofing, and final assembly. These project contexts provided a practical and representative scope to evaluate the applicability of the proposed cost model in addressing real-world challenges faced by developers and cost planners. The chosen case studies highlighted the model's flexibility and ability to adapt to varying project scales and complexities by incorporating diverse configurations and requirements. The modular housing context in the UK was particularly suitable due to its increasing demand for scalable and cost-effective housing solutions. By focusing on modular systems, the research underlined the importance of standardisation and repeatability in achieving cost efficiency while also addressing lifecycle performance metrics such as energy consumption and maintenance.

3.2. Case Analysis

The modular setup for the home designs is illustrated in Figures 1 and 2. The homes' structural framework is primarily steel, with hot- and cold-rolled sections used, depending on material availability. The manufacturing company produces one module daily, employing an integrated process that includes architectural and structural design, planning approval, M&E installations, roofing, and final assembly.

The cases' modular design emphasises efficiency and repeatability, with structural modules predefined to meet GFA requirements. The setup is illustrated in Figures 1 and 2, which showcase the modular layouts for each home type.

The proposed cost modelling framework accounts for performance-related costs, such as energy efficiency and maintenance, to estimate the lifecycle cost of the homes. However, these estimates remain theoretical due to the lack of real-world data during the study. Additionally, the framework does not include land acquisition or site preparation costs. While these elements could be integrated into the model, their exclusion reflects the study's focus on modular construction-specific costs.

This integrated approach highlights the potential of modular design to streamline construction processes, optimise material use, and improve cost modelling. It is a foundation for further research and application of the proposed cost modelling framework.

3.2.1. The Proposed Model

The proposed cost modelling framework (Figure 3) integrates DTs and AI to address the complex requirements of cost estimation, lifecycle analysis, and decision-making in OSC. The model's central tenet is to support modular construction systems by providing real-time insights, predictive cost analysis, and resource optimisation throughout the project lifecycle.

Figure 1. Base modules for three-bed homes.

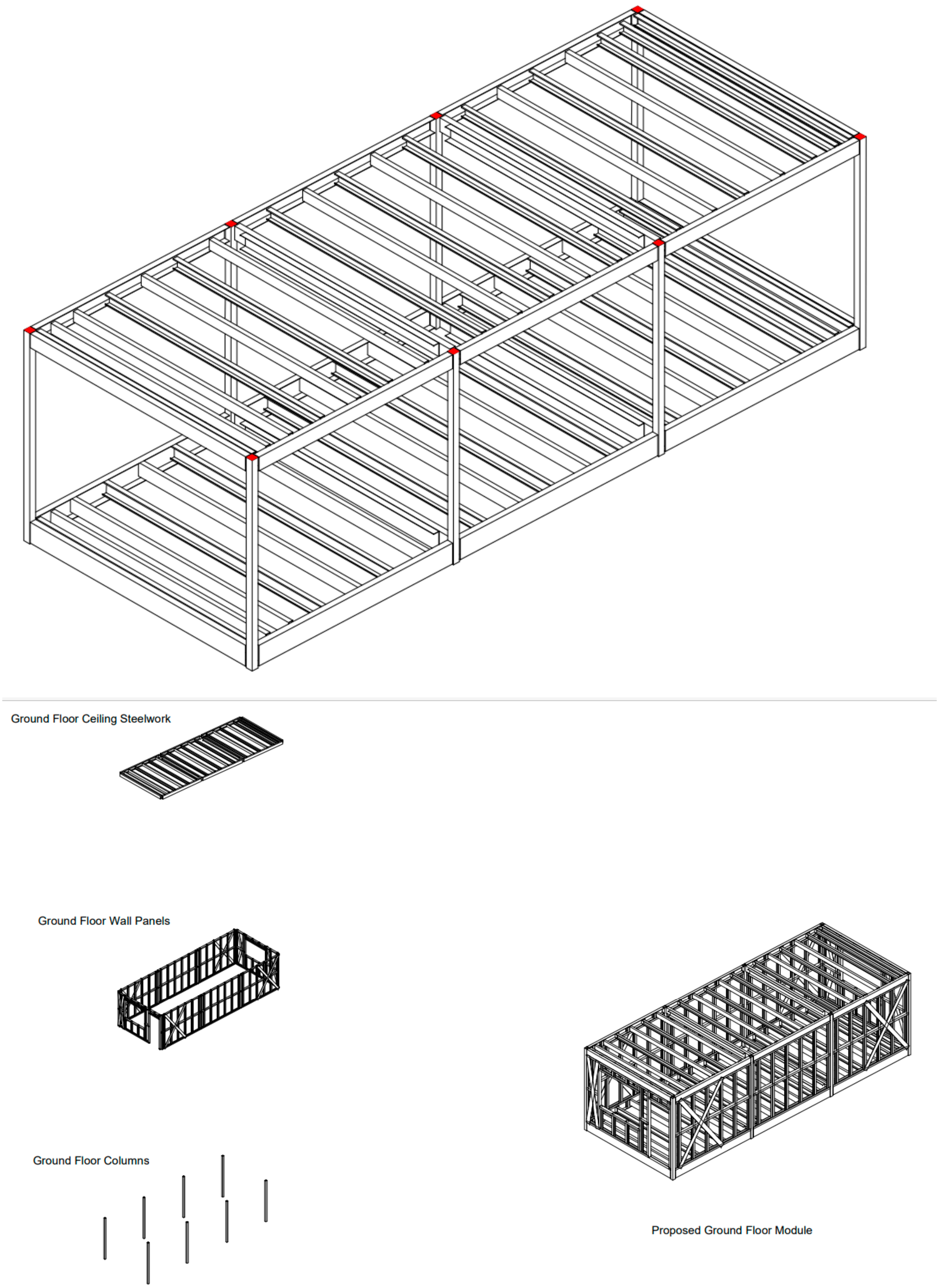

Figure 2. Three-dimensional ground floor base module using revit.

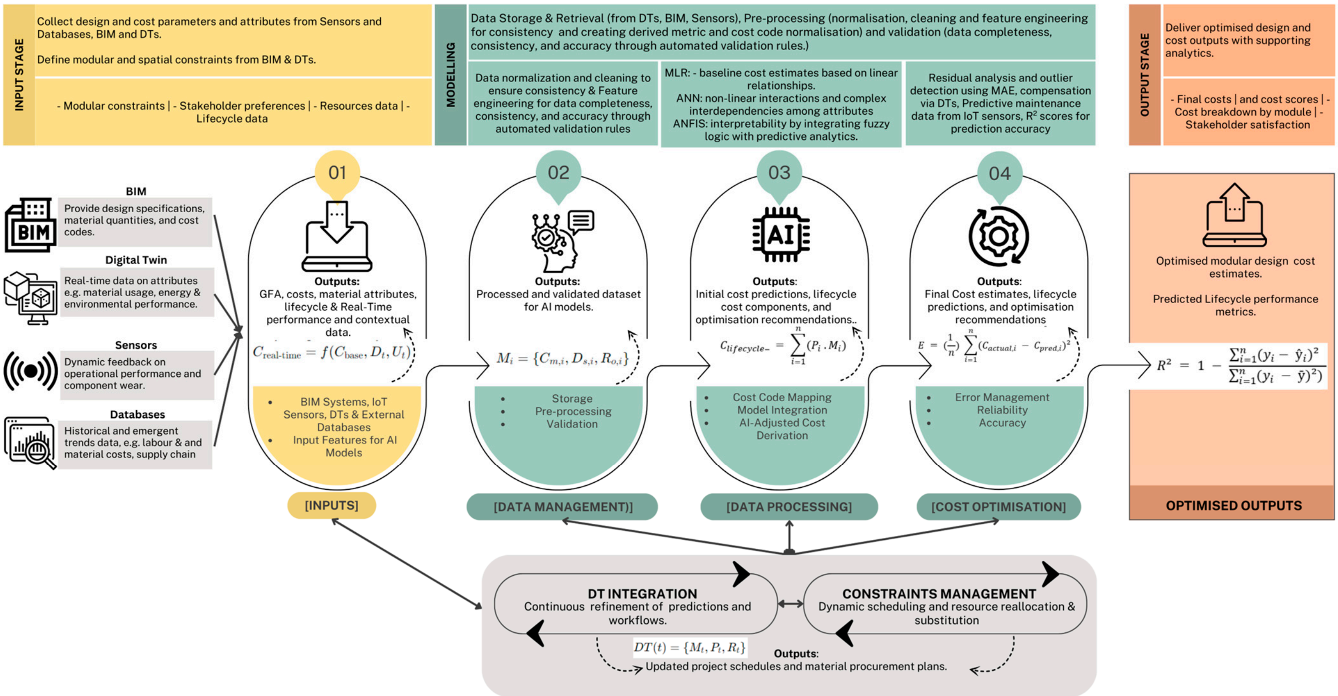

Figure 3. The proposed cost model.

3.2.2. Digital Twin (DT) Component

The Digital Twin is a core element of the model, serving as a dynamic, virtual representation of the modular construction project. It bridges the physical and digital worlds by continuously collecting, updating, and analysing data throughout the construction and operational phases.

The key features of this component include the first real-time data integration—where DT captures data from various sources, including IoT sensors, BIM models, and project management tools. This data contains material usage, construction progress, energy performance, and operational conditions. For instance, sensors track modular components' weight, dimensions, and installation status during transportation and assembly. This data can be integrated through batches or in real time into the AI model as input features or for real-time model updates. Second is lifecycle performance monitoring, where DT tracks the condition of modular components over their lifecycle, identifying maintenance needs and evaluating performance metrics such as energy efficiency and structural integrity. Lastly, the dynamic updates and feedback loops ensure that changes in key functions, such as design, material availability, or construction schedules, are instantly reflected in the DT, enabling real-time cost updates and decision-making. The state of the DT at any time t is represented as: $DT(t) = \{M_t, P_t, O_t, R_t\}$, where $M_t, P_t, O_t,$ and R_t represent key process objectives, i.e., material usage data, production and assembly progress, operational performance metrics, and risk and constraint indicators (e.g., delays and cost overruns) that feed into MLR and ANN algorithms.

3.2.3. AI Decision Models

AI works with DT by processing data, predicting costs, and optimising decision-making processes. This technical integration enhances the model's ability to adapt to dynamic project variables, ensuring efficient resource allocation and improved cost performance. AI uses pre-trained mapping rules and supervised learning models trained on historical data to assign cost codes, building on the initial RICS NRM 1 cost codes such as GFA. Algorithms and MLR serve as a baseline model for interpreting linear relationships between variables, underpinning the AI functionalities (see Section Foundations in AI for Cost Analysis). Through automated cost code mapping, AI models use pre-trained mapping rules or supervised learning models trained on historical data (e.g., NRM 1) to assign cost codes. Real-time data from DTs dynamically updates cost codes, reflecting changes in attributes such as material usage, performance, or schedules. AI employs trained MLR to forecast project cost performance by analysing historical datasets and real-time inputs provided by the DT, such as material cost (C_m)—cost per unit of materials (e.g., steel, insulation); labour hours (H_l)—total hours required for labour, GFA—total gross area in square meters, energy performance (E)—projected annual energy cost, replacement interval (R)—predicted intervals for component replacement). Linear regression predicts the total cost (C_{total}) as a weighted sum of the input variables using the relationship $C_{total} = \beta_0 + \beta_1 C_m + \beta_2 H_l + \beta_3 + \beta_4 E + \beta_5 R$, where β_0 represents the intercept and $\beta_1,\ \beta_2 \ldots..\beta_5$ the coefficients representing the contribution of each feature to the total cost. The model is trained using the dataset to learn the optimal values for β_0 and β_i coefficients. This is done by minimising the Mean Squared Error (MSE) following Equation (2).

On the other hand, ANN captures non-linear relationships and interactions among variables while, at the same time, learning hidden patterns not captured by MLR. ANFIS finally brings interpretability and adaptability to the process, helping with handling uncertainty and imprecision in the variables (e.g., material or labour costs). Mean absolute error (MAE) is then used to measure the average absolute difference between actual and predicted values using the following relationship:

$$MAE = (\frac{1}{n}) \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{4}$$

where n is the number of training samples, y_i the actual value of the $i-th$ sample, and $\hat{y}_i$ is the predicted value for the $i-th$ sample at iteration. The model then uses the R^2 score (Coefficient of Determination) to measure accuracy through variance in the target variable.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{5}$$

where $\overline{y}$ is the mean of actual values, the numerator and denominator the sum of squared residuals (unexplained variance) and total variance, respectively. Residual analysis seeks to identify patterns of bias among attributes. Errors are compensated for by real-time data from the DT, compensating for deviations between predicted and observed values and maintaining continuous data flow for training and retraining the model alongside any emergent attribute data. Alongside period project-based updates, any substantial new data, design changes within BIM or significant deviations in key predicted and actual project costs or performance attributes should also trigger retraining of the model. This ensures improved accuracy, dynamic adaptability, and future-proofing of the model.

3.2.4. Optimisation Objective

The Optimisation Objective is a mathematical concept that takes into account the total project cost (C_{total}) that needs to be minimised as follows:

$$Minimize:\ C_{total} = \sum_{i=1}^{n} (C_{m,i} + C_{l,i} + C_{u,i}) \tag{6}$$

This is subject to $\sum_{j=1}^{m} R_j \leq R_{max}(resource\ constraints)$ and $Q_k \geq Q_{min}(Quality\ Constraints)$; where $C_{m,i},\ C_{l,i},\ C_{u,i} R_j$ and Q_k represent material cost for module i, staff cost for module i, lifecycle cost for module i, available resources (e.g., time, budget) and quality metrics (e.g., thermal performance, durability, constructability), respectively.

The model is tailored to the modular construction paradigm, supporting the decomposition of designs into manageable, standardised components while supporting customisation and adaptability. The key element in this is, first, the standardisation of modules when structural and functional modules are predefined with consistent dimensions and interfaces. This standardisation simplifies cost estimation and material planning. Second is the customisation flexibility, which allows modular components to be configured to meet user-specific requirements without altering the core structural framework. Lastly is the lifecycle cost integration, where the model accounts for costs across the entire modules' lifecycle, including maintenance, retrofitting, and eventual decommissioning. Each module (M_i) is characterised as $(M_i = C_{m,i}, C_{l,i}, D_{s,i}\ R_{o,i}$ and $L_{p,i}$, where $C_{m,i}, D_{s,i}, C_{u,i}\ R_j$ and Q_k are the cost of manufacturing the module, design specifications, operational requirements, and lifecycle performance metrics.

3.2.5. Workflow of the Model

The model follows a structured workflow that integrates DTs, AI, and modular design principles to provide comprehensive cost insights. Step one is for data input, where design specifications, materials data, and project constraints are imported from BIM via Industry Foundation Classes (IFC). This data relates to design and cost parameters, materials, labour, scheduling and process data, energy, lifecycle and environmental performance attributes, real-time data, and derived/engineered parameters. The data is first cleaned for duplicates, missing values, and inconsistencies. It is then normalised and encoded, including feature engineering for derived features such as unit energy costs. Z-score analysis is used to identify outliers that are removed from the data sets that then split between training, validation, and testing sets (70–80%, 10–15%, and 10–15%, respectively). K-fold cross-validation on $k = 5$ sets ensures average performance across the 5 folds, training the model on $k - 1$ and testing it on the rest while keeping the same distribution of critical attributes (e.g., material type, labour hours). This step also includes integrating real-time data streams from sensors (such as for vibration, loading, environment, GPS, or LiDAR) and IoT devices into the DT. Step two is the DT setup, where a DT for the project is constructed, ensuring synchronisation with physical and digital data sources. This stage also helps with dynamic monitoring of material usage, component status, and performance metrics. The next step, step three, is about AI-driven cost analysis. In this stage, the process aims to predict costs using ML algorithms, adjust for real-time data updates, and optimise modular designs and workflows to improve cost performance while maintaining quality and performance. Step four is lifecycle costing, where the modelling uses DT data to calculate lifecycle costs, incorporating factors such as energy performance, maintenance schedules, and upgrade potential. Lastly, step five deals with reporting and recommendations. In this stage, the modelling generates detailed costing reports, including initial construction costs, lifecycle cost breakdowns, and recommendations for cost-saving measures supported by visualisations to support decision-making, such as cost trends and risk analyses.

The validation and feedback process, through case studies, allows for comparing predicted costs with actual project data on the one hand and evaluating time and resource savings in cost estimation and materials planning on the other. A structured long-term performance evaluation process, combined with proactive strategies for maintaining system accuracy, ensures that the model remains reliable, robust, and aligned with the evolving needs of OSC projects. Regular validation, dynamic updates such as from DTs, and stakeholder feedback loops are central to achieving sustained success through integration with emergent capabilities, scheduled system audits, enhancing model resilience through ensemble models, and scheduled and event-driven updates.

3.3. Costing Categories and Methodology

In the initial costing stage, the process utilises GFA measurements as a preliminary basis for cost estimation. Data from the DT provides real-time insights into GFA adjustments and material usage during design iterations. In the approximate costing stage, costs are calculated on a modular basis, considering transportation and manufacturing constraints. In this stage, AI algorithms analyse data from the DT to optimise module-level costs by factoring in efficiencies in production and logistics. Lastly, in the evaluative costing stage, a detailed cost breakdown is performed using elemental costing methods in line with the Royal Institute of Chartered Surveyors (RICS) New Rules of Measurement 1 (NRM 1). In this case, the DT monitors each element's integration into the design, ensuring that costs relating to materials, labour, and assembly are accurately captured. In this stage, AI supports decision-making by simulating multiple scenarios and optimising elemental cost allocations.

3.4. Costing Approach for the Case Studies

An example of the initial elemental costs for two models is summarised in Table 1. They represent costs in year 1 at the prevailing rates, excluding VAT and inflation. The decommissioning costs include those related to demolition and site clearance, demolition management (phase-specific), and demolition overheads (phase-specific), all in present-day value in year 50. These are detailed as per the NRM 1 format (Table 1). The initial costs are based on context-based GFA estimates of 165 sqm and 95 sqm for both models of three- and two-bedroom homes. Table 2 summarises the four models' lifecycle cost breakdown, while Table 3 summarises housing cost estimates with integration of AI and DTs for the two- and three-bedroom home models. Figure 4 is an example of NRM 1 for steel beam, column, and bracing material take-off.

Table 1. Example initial elemental costs for the four models are summarised.

		Discount Rate (%)		**0.060**						
	Model 1—Traditional 2 Bed					**Model 2—Contemporary 2 Bed**				
	Cost Item	**Cost**	**Year**	**Discount Factor**	**Present Value**	**Cost Item**	**Cost**	**Year**	**Discount Factor**	**Present Value**
	Initial cost					Initial cost				
		49,400	0	1.0000	£49,400		58,000	0	1.0000	£58,000
Replacement cost	Replacement cost					Replacement cost				
		2755	20	0.3118	£859		3500	35	0.1301	£455
		2755	40	0.0972	£268					
Maintenance	Cleaning					Cleaning				
		600	annual	16.7619	£10,057		600	annual	16.7619	£10,057
Redecorations and repairing	Redecorations and repairing (£3/m^2)					Redecorations and repairing (£3/m^2)				
		285	10	0.5584	£159		300	10	0.5584	£168
		285	20	0.3118	£89		300	20	0.3118	£94
		285	30	0.1741	£50		300	30	0.1741	£52
		285	40	0.0972	£28		300	40	0.0972	£29
		285	50	0.0543	£15		300	50	0.0543	£16
Repairs	Repairs					Repairs				
		400		16.7619	£6705		180		16.7619	£3017
Energy	Energy					Energy				
		1200		16.7619	£20,114	400			16.7619	£6705
Demolition/ Decommissioning	Demolition/ Decommissioning					Demolition/ Decommissioning				
		0		0.0000	£0	0			0.0000	£0
				Lifecycle cost	£87,744				Lifecycle cost	£78,593

Table 2. A Summary of lifecycle costings for four housing models.

Discount Rate	**6%**								
			Initial Cost	Area (sqm)	Initial Cost/m^2	Replacement Cost/m^2	Repairs	Energy	Redecoration/m^2
			Three Bed Models						
Lifecycle Cost	£133,659	Model A	£120,000	165	500	29	£500	£1600	£3
Lifecycle Cost	£119,528	Model B	£150,000	170	550	35	£200	£500	£3
			Two Bed Models						
Lifecycle Cost	£87,744	Model A	£100,000	95	520	29	£400	£1200	£3
Lifecycle Cost	£78,593	Model B	£125,000	100	580	35	£180	£400	£3

Table 3. Summary of housing cost estimates with integration of AI and DTs.

Type	**Model**	**Approximate Cost (Modular) (£)**	**Initial Cost (GFA m^2) (£)**	**Lifecycle Cost (50 Years) (£)**	**AI-Adjusted Cost (£)**	**Reliability (%)**	**Accuracy (%)**	**DTs Insights**	**AI Adjustments**
Three-Bed Models	Model A	£163,716	£134,216	£210,000	£198,000	97.50%	98%	DT monitors module durability, tracks energy performance, and refines lifecycle costs over time.	AI identifies cost-saving material substitutions and predicts reduced maintenance schedules.
	Model B	£138,563	£117,313	£190,000	£178,500	96%	97%	DT detects wear-and-tear patterns and optimises replacement intervals for structural and functional elements.	AI forecasts operational cost reductions through improved energy efficiency strategies.
Two-Bed Models	Model A	£178,680	£88,080	£190,000	£180,500	98%	96%	DT tracks real-time energy consumption and identifies inefficiencies for proactive adjustments.	AI adjusts repair and energy costs by simulating upgrades to insulation and energy systems.
	Model B	£160,888	£75,988	£180,000	£172,000	97%	95%	DT provides real-time feedback on maintenance needs, reducing unplanned lifecycle costs.	AI optimises lifecycle costs by forecasting component lifespan and recommending pre-emptive replacements.

Lifecycle Cost Assessment (LCCA)

LCCA includes initial costs, plus the operational, maintenance, and replacement costs calculated over a 50-year timeframe ($C_{lifecycle} = C_{initial} + C_{operational} + C_{maintenance} + C_{replacement}$). Cost data are derived from expert input, historical datasets, and real-time performance data collected via DTs. AI predicts future costs based on trends and probability models, integrating them into the total lifecycle cost. The operational costs for energy use, regular maintenance, and repair schedules are analysed. The DT tracks operational efficiency metrics in real time, allowing for adjustments to predicted costs. On the other hand, replacement costs include major replacements planned for key milestones, such as years 20 and 30, based on DT-monitored component wear and tear. MLR, ANN, and ANFIS are integrated to optimise predictive maintenance, materials substitution, supply chain optimisation, operational efficiency, and emergent constraints. Using the relationship $C_{adjusted} = C_{lifecycle} - \triangle C_{AI}$, where $C_{lifecycle}$ is the baseline lifecycle cost and $\triangle C_{AI}$ the total savings or cost adjustments derived by AI, with the overall high-level costs summarised in Table 4.

Discounted Present Value (DPV) accounts for future costs discounted to present-day values using a 6% annual rate (see Table 5). The DPV factor is calculated as follows, and a summary over the 50 years is shown in Table 5. The DPV figures form part of the inputs for AI adjustments during the cost modelling process.

$$DPV = \frac{1}{(1+r)^t} \tag{7}$$

STEEL BEAM MATERIAL TAKEOFF						
MEMBER REF	MEMBER SIZE	MATERIAL/SPEC	NO. OFF	LENGTH (mm)	WEIGHT (T)	NOTES
SB1	CR300x90x3.0	S390	8	(Varies)	0.307	
SB2	2No. CR300x90x3.0 (Back to Back)	S390	4	3853	0.170	Name of section is only for ease of identification on plans and schedules and does not equal the number of beams used. The quantity shown in the 'No. Off' column is correct and weight is based off this.
Ground Floor SSL: 12			12		0.477	
SB3	CR200x90x2.0	S390	8	(Varies)	0.161	
SB4	2No. CR200x90x2.0 (Back to Back)	S390	4	3853	0.089	Name of section is only for ease of identification on plans and schedules and does not equal the number of beams used. The quantity shown in the 'No. Off' column is correct and weight is based off this.
Roof: 12			12		0.250	
Grand total: 24			24		0.726	

STEEL WALL BEAM MATERIAL TAKEOFF						
MEMBER REF	MEMBER SIZE	MATERIAL/SPEC	NO. OFF	LENGTH (mm)	WEIGHT (T)	NOTES
LGS1	CR104x60x1.5	S390	11	(Varies)	0.113	Bottom track and opening cill
Ground Floor SSL: 11			11		0.113	
LGS1	CR100x70x20x2.0	S390	10	(Varies)	0.096	Noggin
LGS1	CR104x60x1.5	S390	11	(Varies)	0.120	Top track and opening lintel
Roof: 21			21		0.216	
Grand total: 32			32		0.330	

STEEL COLUMN MATERIAL TAKEOFF						
MEMBER REF	MEMBER SIZE	MATERIAL/SPEC	NO. OFF	LENGTH (mm)	WEIGHT (T)	NOTES
SC1	SHS100x100x10	S355	8	3028	0.664	
Ground Floor SSL: 8					0.664	
Grand total: 8					0.664	

STEEL WALL COLUMN MATERIAL TAKEOFF						
MEMBER REF	MEMBER SIZE	MATERIAL/SPEC	NO. OFF	LENGTH (mm)	WEIGHT (T)	NOTES
LGS1	CR100x70x20x2.0	S390	73	(Varies)	0.604	
LGS2	CR100x70x20x2.0 (Peri Stud)	S390	53	295	0.065	
Ground Floor SSL: 126					0.669	
LGS2	CR100x70x20x2.0 (Peri Stud)	S390	55	196	0.045	
Roof: 55					0.045	
Grand total: 181					0.713	

STEEL BRACING MATERIAL TAKEOFF						
MEMBER REF	MEMBER SIZE	MATERIAL/SPEC	NO. OFF	LENGTH (mm)	WEIGHT (T)	NOTES
BR	150x2.0	S390	14	(Varies)	0.039	
Ground Floor SSL: 14			14		0.039	
Grand total: 14			14		0.039	

Figure 4. Example NRM 1 for steel beam, column, and bracing material take-off.

Table 4. Example AI-adjusted cost derivation for the three bed model: A design case study.

Cost Category	Baseline Cost (£)	AI Adjustment (£)	Adjusted Cost (£)	Accuracy (%)	Reliability (%)	Remarks
Initial Cost ($C_{adjusted}$)	£134,216	−£1200	£133,016	95%	98%	Cost-saving material substitution for insulation.
Operational Cost ($C_{adjusted}$)	£60,000	−£10,000	£50,000	92%	95%	Energy efficiency improvements reduce annual energy costs.
Maintenance Cost ($C_{adjusted}$)	£10,000	−£2000	£8000	93%	97%	Optimised maintenance schedules reduce costs.
Replacement Cost ($C_{adjusted}$)	£5784	−£1800	£3984	90%	99%	Proactive lifespan extensions for components (e.g., HVAC systems).
Total Lifecycle Cost ($C_{adjusted}$)	£210,000	−£15,000	£195,000	93%	97.5% (Overall)	AI-adjusted cost incorporating all optimizations and savings.

Table 5. Summary of the annual Discount Present Value over a 50-year lifecycle.

	Discount Rate		**6%**		**Total at Year 50**		**16.7077**		
Year	**Discount Rate**	**Year**	**Discount Rate**	**Year**	**Discount Rate**	**Year**	**Discount Rate**	**Year**	**Discount Rate**
0	1.0000								
1	0.9434	11	0.5268	21	0.2942	31	0.1643	41	0.0917
2	0.8900	12	0.4970	22	0.2775	32	0.1550	42	0.0865
3	0.8396	13	0.4688	23	0.2618	33	0.1462	43	0.0816
4	0.7921	14	0.4423	24	0.2470	34	0.1379	44	0.0770
5	0.7473	15	0.4173	25	0.2330	35	0.1301	45	0.0727
6	0.7050	16	0.3936	26	0.2198	36	0.1227	46	0.0685
7	0.6651	17	0.3714	27	0.2074	37	0.1158	47	0.0647
8	0.6274	18	0.3503	28	0.1956	38	0.1092	48	0.0610
9	0.5919	19	0.3305	29	0.1846	39	0.1031	49	0.0575
10	0.5584	20	0.3118	30	0.1741	40	0.0972		

4. Results and Discussion

The LCCA informs the key milestones and applications in the model, which correspond to critical events in the building's lifecycle in years 10, 20, 30, 40, and 50 (for major redecorations). In years 20 and 30, considerations for replacing critical components (e.g., roofing, mechanical systems) guide these assessments. AI models assist in prioritising these milestones by evaluating their impact on overall lifecycle performance and cost efficiency.

The detailed costing process integrates DTs and AI to automate and optimise cost estimation, ensuring the economic viability of modular housing projects and alignment with long-term performance goals. The dynamic nature of this approach allows stakeholders to make informed decisions based on accurate, real-time, and predictive cost data. This approach, for example, supported a cost reduction for Model A (three-bedroom) from 210,000 GBP to 198,000 GBP with AI optimisations of lifecycle costs (see Table 4). Similarly, in Model B (two-bedroom), lifecycle costs were reduced from 180,000 GBP to 172,000 GBP using similar optimisations. These were both against initial costs of 134,216 GBP for the former and 75,988 GBP for the latter. Modular approximations show higher initial efficiency for smaller homes. AI-driven cost adjustments resulted, therefore, in reductions of up to 6–10% in lifecycle costs compared to initial estimates supported by traditional models.

In terms of process substitution, the limited data and modelling localised "hubs and spokes" for processing near project sites pointed to potential reductions in transportation costs of up to 12%. However, this was on a limited component basis.

The proposed costing model can evaluate cost performance while offering opportunities for comparisons between contemporary and traditional modular designs, providing detailed insights into initial and lifecycle costs, optimisation opportunities, and supply chain considerations. The cost performance analysis process involves lifecycle costs, cost breakdown, and optimisation. For lifecycle costing, cost performance is assessed over 50 years, incorporating initial construction and operational costs derived from energy performance, maintenance, and replacement schedules supported by DTs' real-time monitoring of these costs. AI, on the other hand, optimises predictions based on historical and real-time data. The cost breakdown of the initial costs follows the NRM 1 format, including facilitating and building works, contractor preliminaries, overheads and profit, project/design team costs, other development costs, and risk allowances. GFA-based estimation and elemental costing are integrated for comparative analysis, allowing stakeholders to evaluate trade-offs between design options and material choices. Optimisation opportunities allow for elemental parameters, such as window and insulation choices, which are key to cost performance optimisation, to be looked at further. For instance, in the two-bedroom Model A, an energy performance cost of 1200 GBP could be reduced through alternative window or insulation options. DTs provide data-driven insights into the performance implications of such changes, while AI supports comparative cost assessments and decision-making. Overall, the model maintains reliability above 96%, reflecting robust system performance. Two-bedroom Model A achieves a reliability of 98% due to optimised energy and maintenance systems. System accuracy is important in underscoring the confidence levels in the modelling, and it is based on historical data validation, real-time feedback accuracy, and model performance metrics. An overall system accuracy of accuracy levels between 95–98% is registered while 98% registered for Model A (three-bedroom) reflecting a high confidence in lifecycle and AI-adjusted cost predictions of the order ± 5000 GBP or 95% using the expression $\hat{y} \pm z.\sigma$, where $\hat{y}$ is the predicted value, z is the critical value from the standard normal distribution, and σ is the standard error of the prediction.

4.1. Component Catalogue and Modularity in OSC

A component catalogue is central to ensuring the benefits of modularity and repeatability in OSC. This catalogue is ideally collaboratively developed with suppliers and project teams, integrating specialised knowledge to standardise components and processes. However, a lack of widely shared and compatible component catalogues can present challenges, including supply chain risks stemming from dependence on limited vendors and reduced competition among suppliers, leading to increased costs and difficulty efficiently scaling modular processes. These all impact the costing model and process. In mitigation, the model assumes and operates based on advanced sourcing strategies that leverage contracts and bulk purchasing for key components to stabilise costs and reduce risks; clear and transparent processes for supplier collaboration and cost-sharing opportunities; use of DTs to monitor component availability and performance, enabling proactive sourcing decisions; and finally, integration of AI algorithms to analyse supply chain data to identify cost drivers and suggest procurement strategies.

The model similarly assumes long-term collaboration among stakeholders that harnesses shared opportunities, leading to a more profound and continuing understanding of bottlenecks, cost drivers, and skills gaps across the supply chain. It also integrates value-sharing by encouraging transparent communication about base costs, profits, and sourcing challenges as part of the process. Partners prioritise efficiency, innovation, and mutual benefit through these resilient relationships

4.2. Relevance of the Cost Model

The model facilitates a top-down costing approach, enabling market-driven cost estimation based on market analysis and advanced supply chain strategies. Real-time data from DTs highlights critical cost influences throughout the product development cycle, from design to commissioning. At the same time, DTs enable collaborative cost tracking and adjustments during iterative processes. The power of AI in this process is to support market analysis by identifying cost trends and forecasting procurement needs. Similarly, predictive analytics help secure essential materials and components at optimised prices, embedding competitiveness early in the process.

The power of AI and transparency of DTs can support elemental and component substitution that fosters cost performance. Alternative materials and components can be chosen to reduce costs and increase flexibility in OSC systems, enabled by AI's power to identify and evaluate cost drivers in elemental and component choices, leveraging historical and real-time data for accurate cost estimation. A Work Breakdown Structure (WBS) approach can, for example, highlight critical project processes, such as cost optimisation, with algorithmic scaling for adjustments. This can be a key driver for overall project performance as part of a centralised component catalogue, maintained with inputs from DTs, ensuring ready access to alternative options for materials and parts. AI optimisations can support the substitution process by recommending cost-effective alternatives while maintaining performance standards.

The model highlights key processes during cost modelling, ultimately allowing process substitution to maximise efficiency and optimise costs. The elemental NRM 1 approach can, for example, allow for substituting hot-rolled with heat-rolled steel components or the dynamic balance between spoke-and-hub production processes for key modular components, enabled by DTs monitoring for process efficiency and dynamic analysis of production alternatives. At the same time, AI algorithms evaluate the cost and feasibility of process substitutions, recommending strategies that align with project goals.

The model provides advanced capabilities for cost optimisation, enabling iterative refinement of unit, component, and process costs. DTs are essential in this process, helping generate real-time performance data and allowing continuous cost recalibrations based on changing project conditions. At the same time, AI simulations facilitate comparative assessments of key inputs such as components, materials, and other processes, identifying cost-saving opportunities. AI-driven optimisation aligns cost strategies with project processes, objectives, and constraints.

As previously pointed out, the model's approach is based on an optimised component catalogue to support strategic sourcing and supply chain management decisions. This premise presents opportunities for DTs to track component availability and performance, informing timely procurement decisions. On the other hand, it analyses supply chain data to identify cost-effective suppliers and sourcing opportunities. At the same time, advanced algorithms help determine whether to use build-to-specification or design-for-manufacture approaches, reducing lead times and costs.

As cost performance can influence value performance, the model highlights opportunities for value generation during front-end design stages, ensuring cost decision-making aligns with value-added processes and features. Using DTs, simulations in this project phase can optimise design performance, identifying synergies between cost reduction and value creation. Similarly, AI in this stage facilitates evaluating multiple design iterations to balance cost efficiency with value addition. If costs fall below baseline estimates, AI suggests reinvestments in value-enhancing features. Conversely, AI highlights opportunities to streamline design features if costs exceed thresholds.

5. Conclusions

Cost performance is one of the key benefits that OSC systems bring to AEC.

Real-time data collected through DTs enhances lifecycle costing by continuously monitoring operational and performance costs. For example, DTs can track energy efficiency improvements resulting from material substitutions, feeding this data into the model for iterative cost optimisation. On the other hand, AI algorithms can support multiple simulations of multiple cost scenarios, enabling stakeholders to evaluate the implications of various design and material choices. This approach ensures cost performance is aligned with immediate project goals and long-term lifecycle requirements.

Integrating DTs and AI offers a powerful solution to overcome inefficiencies in traditional OSC cost modelling systems. Dynamic, adaptive, and efficient cost modelling frameworks can be created by combining DTs' real-time data capabilities with AI's predictive and optimisation strengths. This research addresses the identified gaps by proposing a model that advances cost modelling through improved efficiencies and adaptability of OSC design and costing processes.

This research highlights the industry's constant challenge to balance project performance, lead times, and cost efficiency. The proposed model supports this balance by offering precise cost estimation and identifying shared opportunities for stakeholders to improve project outcomes. Accurate, real-time information forms the cornerstone of this approach, fostering transparency and collaboration across the supply chain.

Long-term relationships and stakeholder collaboration emerge as critical components of the proposed model, just as hubs and spokes' integral role is decentralised processing, reducing logistical challenges and associated costs. By aligning interests and emphasising cooperation during the project front end, the model promotes shared benefits, enhances trust, and drives continuous improvement in OSC processes. This research concludes that integrating DTs and AI into cost modelling represents a transformative step toward improving cost accuracy, lifecycle performance, and industry collaboration in modular construction.

AI has demonstrated significant potential in many processes, and integrating complementary technologies could address critical gaps in cost estimation, lifecycle analysis, and decision-making, paving the way for more efficient and adaptive modular construction systems. The model, however, still faced limitations relating to, among other things, integrating DTs and modular workflows to enhance decision-making across project phases, which still need to be understood further. Similarly, the accuracy of AI models is highly dependent on the quality and quantity of input data. In many cases, incomplete or inconsistent data from construction projects limited the model's performance. Addressing these gaps requires the development of more robust data collection and management practices. While the model incorporated lifecycle cost components such as energy efficiency and maintenance, it did not fully explore other critical factors like adaptability and sustainability in modular construction. Extending the model to include these dimensions will provide a more comprehensive cost analysis. The model's application was tested on two housing cases, which means that its scalability to more complex, multi-phase projects with larger datasets has not yet been fully validated. Lastly, the adoption and usability across different contexts are limited by the requirement for specialised skills and knowledge to operate, implement, and maintain the system effectively.

Future Research Opportunities

Further research is needed to refine the integration of DTs with the AI-driven cost model, particularly to improve decision-making across all project phases, from design to decommissioning. This includes exploring advanced techniques for real-time data synchronisation and analytics across the project's full life. Secondly, standardised protocols in data sets and improving data quality will significantly enhance the accuracy of the AI model. Future studies could leverage federated learning or decentralised data-sharing frameworks to mitigate data privacy and availability concerns. Lastly, to enhance the model's generalisation, a broader range of modular construction project contexts across the high-density and commercial buildings sector will validate its scalability and adaptability.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the author.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Gusmao Brissi, S.; Debs, L.; Elwakil, E. A Review on the Factors Affecting the Use of Offsite Construction in Multifamily Housing in the United States. *Buildings* **2021**, *11*, 5. [CrossRef]
2. Serugga, J.; Kagioglou, M.; Tzortzopoulos, P. Value generation in front-end design of social housing with qfd and multiattribute utility theory. *J. Constr. Eng. Manag.* **2020**, *146*, 04020019. [CrossRef]
3. Sutrisna, M.; Ramnauth, V.; Zaman, A. Towards adopting off-site construction in housing sectors as a potential source of competitive advantage for builders. *Archit. Eng. Des. Manag.* **2022**, *18*, 165–183. [CrossRef]
4. Obi, L.; Arif, M.; Goulding, J. Low-cost housing: A cost management model for process integration and evaluation. *Archit. Eng. Des. Manag.* **2020**, *16*, 411–425. [CrossRef]
5. Akbarieh, A.; Jayasinghe, L.B.; Waldmann, D.; Teferle, F.N. BIM-based end-of-lifecycle decision making and digital deconstruction: Literature review. *Sustainability* **2020**, *12*, 2670. [CrossRef]
6. Hussein, M.; Zayed, T. Critical factors for successful implementation of just-in-time concept in modular integrated construction: A systematic review and meta-analysis. *J. Clean. Prod.* **2021**, *284*, 124716. [CrossRef]
7. Hyun, H.; Kim, H.; Lee, H.-S.; Park, M.; Lee, J. Integrated Design Process for Modular Construction Projects to Reduce Rework. *Sustainability* **2020**, *12*, 530. [CrossRef]
8. Tan, T.; Mills, G.; Papadonikolaki, E.; Li, B.; Huang, J. Digital-enabled Design for Manufacture and Assembly (DfMA) in offsite construction: A modularity perspective for the product and process integration. *Archit. Eng. Des. Manag.* **2023**, *19*, 267–282. [CrossRef]
9. Piroozfar, P.A.; Piller, F.T. *Mass Customisation and Personalisation in Architecture and Construction*; Routledge: New York, NY, USA, 2013.
10. Xue, H.; Zhang, S.; Su, Y.; Wu, Z.; Yang, R.J. Effect of stakeholder collaborative management on off-site construction cost performance. *J. Clean. Prod.* **2018**, *184*, 490–502. [CrossRef]
11. Obi, L.I.; Awuzie, B.; Islam, R.; Gupta, A.D.; Walton, R. Critical success factors for cost management in public-housing projects. *Constr. Innov.* **2021**, *21*, 625–647. [CrossRef]
12. Sutrisna, M.; Cooper-Cooke, B.; Goulding, J.; Ezcan, V. Investigating the cost of offsite construction housing in Western Australia. *Int. J. Hous. Mark. Anal.* **2019**, *12*, 5–24. [CrossRef]
13. Turner, C.; Oyekan, J.; Stergioulas, L.K. Distributed Manufacturing: A New Digital Framework for Sustainable Modular Construction. *Sustainability* **2021**, *13*, 1515. [CrossRef]
14. Skačkauskienė, I.; Vestertė, J. Discourse on service modularity: Investigating service delivery process. In Proceedings of the International Scientific Conference "Contemporary Issues in Business, Management and Economics Engineering", Vilnius, Lithuania, 9–10 May 2010.
15. Blackenfelt, M. *Managing Complexity by Product Modularisation*; Tekniska högskolan i Stockholm, Institutionen för maskinkonstruktion: Stockholm, Sweden, 2001.
16. Abdelmohsen, S.; Lee, J.; Eastman, C. Automated cost analysis of concept design BIM models. In *Designing Together: CAAD Futures*; Presses Universitaires de Liège: Liège, Belgium, 2011; pp. 403–418.
17. Bayliss, S.; Bergin, R. *The Modular Housing Handbook*; Routledge: Oxfordshire, UK, 2020.
18. Lindblad, F.; Magnusson, B.; Luu, A.; Ragnarsson, J. Information Flow Optimisation: Enabling Standardisation towards Modular Building Methods of Wood-Building Solutions. *Int. J. Innov. Manag. Technol.* **2018**, *9*, 232–239. [CrossRef]
19. Wuni, I.Y.; Shen, G.Q.; Osei-Kyei, R. Quantitative evaluation and ranking of the critical success factors for modular integrated construction projects. *Int. J. Constr. Manag.* **2022**, *22*, 2108–2120. [CrossRef]
20. Mignacca, B.; Locatelli, G.; Velenturf, A. Modularisation as enabler of circular economy in energy infrastructure. *Energy Policy* **2020**, *139*, 111371. [CrossRef]
21. Salama, T.; Salah, A.; Moselhi, O. Integration of offsite and onsite schedules in modular construction. In Proceedings of the ISARC, International Symposium on Automation and Robotics in Construction, Taipei, Taiwan, 28 June–1 July 2017.

22. Schwarz, C.; Wang, Z. The role of digital twins in connected and automated vehicles. *IEEE Intell. Transp. Syst. Mag.* **2022**, *14*, 41–51. [CrossRef]
23. Pan, Y.; Zhang, L. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Autom. Constr.* **2021**, *122*, 103517. [CrossRef]
24. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Delgado, J.M.D.; Bilal, M.; Akinade, O.O.; Ahmed, A. Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *J. Build. Eng.* **2021**, *44*, 103299. [CrossRef]
25. Hussein, M.; Eltoukhy, A.E.; Karam, A.; Shaban, I.A.; Zayed, T. Modelling in off-site construction supply chain management: A review and future directions for sustainable modular integrated construction. *J. Clean. Prod.* **2021**, *310*, 127503. [CrossRef]
26. Hsu, P.-Y.; Aurisicchio, M.; Angeloudis, P. Risk-averse supply chain for modular construction projects. *Autom. Constr.* **2019**, *106*, 102898. [CrossRef]
27. Mao, C.; Xie, F.; Hou, L.; Wu, P.; Wang, J.; Wang, X. Cost analysis for sustainable off-site construction based on a multiple-case study in China. *Habitat Int.* **2016**, *57*, 215–222. [CrossRef]
28. Pan, W.; Parker, D.; Pan, M. Problematic interfaces and prevention strategies in modular construction. *J. Manag. Eng.* **2023**, *39*, 05023001. [CrossRef]
29. Conte, M.; Echeveste, M.E.; Formoso, C.T.; Bazzan, J. Synergies between Mass Customisation and Construction 4.0 Technologies. *Buildings* **2022**, *12*, 1896. [CrossRef]
30. Kamali, M.; Hewage, K. Life cycle performance of modular buildings: A critical review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 1171–1183. [CrossRef]
31. Jayawardana, J.; Sandanayake, M.; Kulatunga, A.K.; Jayasinghe, J.; Zhang, G.; Osadith, S.U. Evaluating the circular economy potential of modular construction in developing economies—A life cycle assessment. *Sustainability* **2023**, *15*, 16336. [CrossRef]
32. Serugga, J.; Kagioglou, M.; Edwards, D.; Talebi, S.; Johns, N. Key influences to cost modelling and analysis in off-site construction: Research trends and GAP analysis. *Archit. Eng. Des. Manag.* **2023**, *20*, 1335–1356. [CrossRef]
33. Xu, S. Automatic Cost Estimation of Construction Project Based on Building Information Modelling: A Knowledge-Based System Approach. Ph.D. Thesis, University of Reading, Reading, UK, 2015.
34. Huynh, D.; Nguyen-Ky, S. Engaging building automation data visualisation using building information modelling and progressive web application. *Open Eng.* **2020**, *10*, 434–442. [CrossRef]
35. Sacks, R.; Bloch, T.; Katz, M.; Yosef, R. Automating design review with artificial intelligence and BIM: State of the art and research framework. In Proceedings of the ASCE International Conference on Computing in Civil Engineering 2019, Atlanta, GA, USA, 17–19 June 2019; pp. 353–360.
36. Ismanov, I.; Qayumov, N.; Mukhamadjonova, D.; Akhmadaliyev, B. AI and Cost Management: Strategies for Reducing Expenses and Improving Profit Margins in Business. In Proceedings of the 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), Chikkaballapur, India, 18–19 April 2024; pp. 1–7.
37. Batty, M. *Digital Twins*; SAGE Publications; Sage: London, UK, 2018; Volume 45, pp. 817–820.
38. Kor, M.; Yitmen, I.; Alizadehsalehi, S. An investigation for integration of deep learning and digital twins towards Construction 4.0. *Smart Sustain. Built Environ.* **2023**, *12*, 461–487. [CrossRef]
39. Omrany, H.; Al-Obaidi, K.M.; Husain, A.; Ghaffarianhoseini, A. Digital twins in the construction industry: A comprehensive review of current implementations, enabling technologies, and future directions. *Sustainability* **2023**, *15*, 10908. [CrossRef]
40. Segovia, M.; Garcia-Alfaro, J. Design, modeling and implementation of digital twins. *Sensors* **2022**, *22*, 5396. [CrossRef]
41. Zhang, J.; Cheng, J.C.; Chen, W.; Chen, K. Digital twins for construction sites: Concepts, LoD definition, and applications. *J. Manag. Eng.* **2022**, *38*, 04021094. [CrossRef]
42. Hou, C.; Remøy, H.; Wu, H. Digital twins to enable smart heritage facilities management: A systematic literature review. In Proceedings of the 27th Pacific Rim Real Estate Society Annual Conference, Pacific Rim Real Estate Society (PRRES), Sydney, Australia, 15–17 January 2023.
43. Deng, M.; Menassa, C.C.; Kamat, V.R. From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *J. Inf. Technol. Constr.* **2021**, *26*, 58–83. [CrossRef]
44. Jiang, Y.; Li, M.; Guo, D.; Wu, W.; Zhong, R.Y.; Huang, G.Q. Digital twin-enabled smart modular integrated construction system for on-site assembly. *Comput. Ind.* **2022**, *136*, 103594. [CrossRef]
45. van Dinter, R.; Tekinerdogan, B.; Catal, C. Predictive maintenance using digital twins: A systematic literature review. *Inf. Softw. Technol.* **2022**, *151*, 107008. [CrossRef]
46. You, Y.; Chen, C.; Hu, F.; Liu, Y.; Ji, Z. Advances of digital twins for predictive maintenance. *Procedia Comput. Sci.* **2022**, *200*, 1471–1480. [CrossRef]
47. Drobnyi, V.; Hu, Z.; Fathy, Y.; Brilakis, I. Construction and maintenance of building geometric digital twins: State of the art review. *Sensors* **2023**, *23*, 4382. [CrossRef] [PubMed]

48. Purcell, W.; Neubauer, T.; Mallinger, K. Digital Twins in agriculture: Challenges and opportunities for environmental sustainability. *Curr. Opin. Environ. Sustain.* **2023**, *61*, 101252. [CrossRef]
49. Ye, X.; Du, J.; Han, Y.; Newman, G.; Retchless, D.; Zou, L.; Ham, Y.; Cai, Z. Developing human-centered urban digital twins for community infrastructure resilience: A research agenda. *J. Plan. Lit.* **2023**, *38*, 187–199. [CrossRef] [PubMed]
50. Kolbachev, E.; Zharov, V.; Tsukerman, V. Cost management for PLM systems: A way to improve the competitiveness in digital economy. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *497*, 012076. [CrossRef]
51. Canedo, A. Industrial IoT lifecycle via digital twins. In Proceedings of the Eleventh IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, Pittsburgh, PA, USA, 1–7 October 2016; p. 1.
52. Aheleroff, S.; Mostashiri, N.; Xu, X.; Zhong, R.Y. Mass personalisation as a service in industry 4.0: A resilient response case study. *Adv. Eng. Inform.* **2021**, *50*, 101438. [CrossRef]
53. Margaria, T.; Ryan, S. Data and Data Management in the Context of Digital Twins. In *The Digital Twin*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 253–278.
54. Pattyam, S.P. Advanced AI Algorithms for Predictive Analytics: Techniques and Applications in Real-Time Data Processing and Decision Making. *Distrib. Learn. Broad Appl. Sci. Res.* **2019**, *5*, 359–384.
55. Deekshith, A. Integrating AI and Data Engineering: Building Robust Pipelines for Real-Time Data Analytics. *Int. J. Sustain. Dev. Comput. Sci.* **2019**, *1*, 1–35.
56. Mirindi, D.; Sanders, T.N.; Hunter, J. Integration of Artificial Intelligence and Smart Technologies in Offsite Construction: A Comprehensive Review. In Proceedings of the 2024: Transforming Construction with Off-site Methods and Technologies (TCOT), Fredericton, NB, Canada, 20–22 August 2024.
57. Waas, B. *Artificial Intelligence and Labour Law*; Hugo Sinzheimer Institute for Labour and Social Security Law: Frankfurt, Germany, 2022.
58. Niederman, F. Project management: Openings for disruption from AI and advanced analytics. *Inf. Technol. People* **2021**, *34*, 1570–1599. [CrossRef]
59. Zheng, J.; Dagnino, A. An initial study of predictive machine learning analytics on large volumes of historical data for power system applications. In Proceedings of the 2014 IEEE International Conference on Big Data (Big Data), Washington, DC, USA, 27–30 October 2014; pp. 952–959.
60. McDonnell, M.D.; Arnaldo, D.; Pelletier, E.; Grant-Jacob, J.A.; Praeger, M.; Karnakis, D.; Eason, R.W.; Mills, B. Machine learning for multi-dimensional optimisation and predictive visualisation of laser machining. *J. Intell. Manuf.* **2021**, *32*, 1471–1483. [CrossRef]
61. Bassey, K.E.; Juliet, A.R.; Stephen, A.O. AI-Enhanced lifecycle assessment of renewable energy systems. *Eng. Sci. Technol. J.* **2024**, *5*, 2082–2099. [CrossRef]
62. Ergazakis, E.; Ergazakis, K.; Metaxiotis, K.; Bellos, E.; Leopoulos, V. An ai-based decision support system for designing knowledge-based development strategies. *Int. J. Intell. Syst. Technol. Appl.* **2008**, *5*, 201–233. [CrossRef]
63. Padmanabhan, R.; Meskin, N.; Khattab, T.; Shraim, M.; Al-Hitmi, M. Reinforcement learning-based decision support system for COVID-19. *Biomed. Signal Process. Control* **2021**, *68*, 102676. [CrossRef] [PubMed]
64. Aziz, S.; Dowling, M. Machine learning and AI for risk management. In *Disrupting Finance: FinTech Strategy 21st Century*; Palgrave Pivot: Cham, Switzerland, 2019; pp. 33–50.
65. Khodabakhshian, A.; Puolitaival, T.; Kestle, L. Deterministic and probabilistic risk management approaches in construction projects: A systematic literature review and comparative analysis. *Buildings* **2023**, *13*, 1312. [CrossRef]
66. Ghali, U.M.; Usman, A.; Degm, M.A.A.; Alsharksi, A.N.; Naibi, A.M.; Abba, S. Applications of artificial intelligence-based models and multi-linear regression for the prediction of thyroid stimulating hormone level in the human body. *Int. J. Adv. Sci. Technol.* **2020**, *29*, 3690–3699.
67. Bode, J. Neural networks for cost estimation: Simulations and pilot application. *Int. J. Prod. Res.* **2000**, *38*, 1231–1254. [CrossRef]
68. Matel, E.; Vahdatikhaki, F.; Hosseinyalamdary, S.; Evers, T.; Voordijk, H. An artificial neural network approach for cost estimation of engineering services. *Int. J. Constr. Manag.* **2022**, *22*, 1274–1287. [CrossRef]
69. Hassan, A.; El-Rayes, K.; Attalla, M. Stochastic scheduling optimization of repetitive construction projects to minimize project duration and cost. *Int. J. Constr. Manag.* **2023**, *23*, 1447–1456. [CrossRef]
70. Rezakhani, P. Hybrid fuzzy-Bayesian decision support tool for dynamic project scheduling and control under uncertainty. *Int. J. Constr. Manag.* **2022**, *22*, 2864–2876. [CrossRef]
71. Posada, H.; Chacón, R.; Ramonell, C. Job roles for digital twinning building construction processes. Introducing the digital twin manager position. *Int. J. Constr. Manag.* **2024**, 1–17. [CrossRef]
72. Alzraiee, H. Cost estimate system using structured query language in BIM. *Int. J. Constr. Manag.* **2022**, *22*, 2731–2743. [CrossRef]
73. Zhou, J.; Tam, V.W.; Qin, Y.; Illankoon, C. A critical review and comparative analysis of cost management on prefabricated construction research (2000–2022). *Int. J. Constr. Manag.* **2024**, *24*, 997–1006. [CrossRef]

74. Hu, H.; Jiang, S.; Goswami, S.S.; Zhao, Y. Fuzzy Integrated Delphi-ISM-MICMAC Hybrid Multi-Criteria Approach to Optimize the Artificial Intelligence (AI) Factors Influencing Cost Management in Civil Engineering. *Information* **2024**, *15*, 280. [CrossRef]
75. Du, J.; Jing, H.; Castro-Lacouture, D.; Sugumaran, V. Multi-agent simulation for managing design changes in prefabricated construction projects. *Eng. Constr. Archit. Manag.* **2019**, *27*, 270–295. [CrossRef]